Volume-Synchronized Probability of Informed Trading (VPIN), Market Volatility, and High-Frequency Liquidity

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Abstract

We assess the predictive ability of three VPIN metrics on the basis of two highly volatile market events of China, and examine the association between VPIN and toxic-induced volatility through conditional probability analysis and multiple regression. We examine the dynamic relationship on VPIN and high-frequency liquidity using Vector Auto-Regression models, Granger Causality tests, and impulse response analysis. Our results suggest that Bulk Volume VPIN has the best risk-warning effect among major VPIN metrics. VPIN has a positive association with market volatility induced by toxic information flow. Most importantly, we document a positive feedback effect between VPIN and high-frequency liquidity, where a negative liquidity shock boosts up VPIN, which, in turn, leads to further liquidity drain. Our study provides empirical evidence that reflects an intrinsic game between informed traders and market makers when facing toxic information in the high-frequency trading world.

Key Words: VPIN; market volatility; high-frequency liquidity.

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I. Introduction

In the current financial markets, traditional low-frequency trading stage has turned into the high-frequency era. Acting a crucial role in the provision of liquidity, high frequency trading (HFT) has drawn continuous attention on the research of market microstructure theory. While HFT does cultivate the booming of current financial markets, we cannot ignore the problems caused by this prevalent mechanism. On May 6th, 2010, Dow Jones Industrial Average plunged 1010.14 points and then recovered in a few minutes. As this high volatile event is induced by the information unknown to outside investors and unusual liquidity fluctuation, the fast-growing trading mechanism incurs queries on financial risk management system. Investors believe that HFT has made the market less fair than before (WSJ, 2012); Regulators reckon that high frequency trading firms should obey trading obligations to support the stability of financial markets (SEC, 2010; WSJ, 2012); Experts concern that HFT undermines integrity of market and causes the market to lose credibility (FT, 2012; WSJ, 2014).

A better risk-warning system for unusual market volatile conditions under HFT mechanism is pressingly needed to be explored. The major issue is the measurement of informed trading. In an indirect way, bid-ask spread is the first proxy to describe information asymmetry in the previous literature (Bagehot, 1971, Copeland & Galai, 1983, Glosten & Milgrom, 1985). Later on, direct measures of information asymmetry are proposed. PIN (Probability of Information-based Trading) is a prominent that uses the probability of informed trading to quantitatively measure the adverse selection risk (Easley et al., 1996). A new metric of VPIN (Volume-

Synchronized Probability of Informed Trading) is constructed subsequently, serving as a time-varying update and a high-frequency estimate of PIN (Easley et al., 2011).

Using their proposed VPIN metric, Easley et al. (2011c) notice the importance of market liquidity and present a possible explanation of the Flash Crash Event. They state that there exists an evaporation of liquidity in the marketplace during the event period. This severe liquidity mismatch is exacerbated by the withdrawal of liquidity from electronic market makers and the change on their trading strategies. Easley et al. (2012a) also present a possible explanation for the VPIN metric that high toxicity will cause losses to liquidity providers. Therefore, when facing high toxicity or namely high VPIN, liquidity providers may drop out of the market thus liquidity will decrease. The withdrawal of market makers causes VPIN to shoot up further, showing an even higher level of information toxicity, which will drive more liquidity providers away from making the market. An extreme level of VPIN will result in trading halt because no market makers are willing to provide liquidity. Such a downward spiral or positive feedback effect between information toxicity and market liquidity is generally viewed as an intuitive explanation of the Fat Finger Event. However, the market microstructure literature has not yet conducted empirical analysis that formally examines the feedback effect between VPIN and liquidity. Our thesis aims to fill this gap through an empirical study to formally test the intrinsic relationships between liquidity and VPIN metrics under the high-frequency trading framework.

Liquidity is characterized by a high level of trading activity. It is the degree to which an asset or security can be bought or sold in the market without affecting the price of assets. In the previous literature, low-frequency liquidity proxies and high-frequency liquidity benchmarks are defined in terms of transaction costs (such as bid-ask spreads and the price impact). In our thesis, we focus on high-frequency liquidity measures that are more suitable to examine their association with VPIN. In the first part of the thesis, we aim to choose a best VPIN calculation algorithm that has the most accurate risk-warning effect. This part serves as the basis for the thesis by choosing a VPIN metric that has the most accurate forecasting ability and demonstrating the effectiveness of VPIN on the Chinese market. In the second part of the thesis, we use the most accurate VPIN metric to test the empirical relations between VPIN and high-frequency liquidity. Furthermore, we attempt to offer an economic interpretation of the empirically identified relationship.

The use of Chinese market data is motivated by the two influential events of China, both with extremely high volatility and huge liquidity fluctuation. Similar to the 2010 U.S. Flash Crash, the 'Fat Finger Event' of Chinese Stock Index Futures happened on August 16, 2013. It was incurred by institutional traders from China Everbright Securities who mistakenly submitted billions of purchase orders for index future shares. This uninformed trading error shocked the market with a rollercoaster movement in a single transaction day, leading the index to dramatically rise 5.62% in minutes and then go through a huge plunge after the mistake was discovered. The second liquidity event, namely "Money Shortage Event", also had a dramatic effect on the Chinese market, causing several times of market fluctuations during two transaction weeks of June 2013. The money shortage occurred when the benchmark money market rates of China shot up in June 2013, as the People's Bank of China declined to extend bank credits, suddenly causing a liquidity shortage shock in the entire market. Inspired by the idea of Easley et al (2012a), when informed traders trigger an unusual liquidity fluctuation in the market, market makers will change their trading strategies by widening up the bid-ask spreads. Such market making behaviors rise up the measure of informed trading such as VPIN, and in turn refrain market makers from providing further liquidity to the market. Therefore, we conjecture a two-way feedback effect between VPIN and high-frequency liquidity as follows. On one hand, if there exists informed trading in the market, VPIN will rise as a result of liquidity deficiency; on the other hand, as VPIN rises to a high level, it will have a positive feedback effect on liquidity and make it decrease even further. This thesis aims to empirically examine this two-way feedback effect using the VAR methodology and impulse-response analysis.

This thesis contributes to the microstructure literature along the following two lines. The first is to conduct an out-of-sample test for the validity of VPIN, in order to provide new evidence on the current debate with regard to the effectiveness of VPIN, as well as to choose the best VPIN metric for our liquidity research. The uniqueness of our data plays an important role in the contribution to the VPIN research, due to the speculative and manipulative nature of the Chinese market compared to the U.S. market. Informed trading and the magnitude of liquidity events should be more pronounced in such a market. If VPIN is indeed an effective measure of high-frequency informed trading, we should observe that VPIN exhibits a strong pattern of information toxicity with respect to our high-frequency liquidity measures.

Specifically, based on the two highly volatile events in the Chinese market, we seek a metric of VPIN that has the most predictive effectiveness of the market. We extend the previous research by adding the Lee-Ready level-2 trade classification algorithm into the evaluation, and hold a comparative study of three methods for the computation of VPIN. The three major trade classification algorithms are Lee-Ready Classification (LR, 1991), Tick Rule Classification (TR, 1987), and Bulk Volume Classification (BV, 2012). For these three algorithms, we test whether CDF lines of

VPIN have clearly reached a high level prior to the occurrence of high volatile events; namely which VPIN metric has the most accurate predictive effect.

The first part of the thesis further contributes to a recent debate on the effectiveness of VPIN. Easley et al. (2012a) argue that VPIN successfully predicts the high volatile activities of the market more than one hour in advance. They document that VPIN has a positive association with market volatility. However, in the analysis of Andersen and Bondarenko (2014), VPIN metric does not show a clear association with the future volatility. In this regard, this thesis attempts to shed new light on this debate using the Chinese market data in an out-of-sample setting.

The second and more important contribution of the thesis is to examine the empirical relationship between VPIN and high-frequency market liquidity. Although the two-way feedback effect of informed trading and market liquidity has been theoretically presented and intuitively described in the literature, to our knowledge, there seems to be no formal empirical analysis on this positive feedback mechanism in the high-frequency setting. To shed lights on this issue, the second part of the thesis employs the Vector Auto-Regression (VAR) model and impulse-response analysis to examine the intrinsic relationship of VPIN and market liquidity.

Our first finding in the thesis suggests that the BV-VPIN metric has the best risk-warning effect among the three VPIN calculation algorithms. In our two-year sample, VPIN gets the highest values on August 16, 2013 and in June 2013, which correspond perfectly to the two periods of high volatile events in the Chinese Stock Index Futures market. In the Fat Finger Event, we notice that the CDF lines of BV-VPIN kept rising from 10:09 a.m., crossed the threshold of 0.8 about 15 minutes ahead of the huge price rise of 5.62% at 11:05 a.m., and stayed at high level through the huge plunge in the afternoon. However, TR-VPIN and LR-VPIN did not show a stable predictive effectiveness of this intraday event. Similarly, in the Money Shortage Event, the CDF lines of BV-VPIN had already attained an uncommonly high level of 0.9 before the plunge on June 24 and stayed at the high level till the end of June 25, indicating an abnormally high level of information risk in the market. On a comparative basis, the CDF line of TR-VPIN fluctuated at a normal level during the volatile days and rose to a relatively high level after the plunge, whereas the CDF line of LR-VPIN did not exhibit a clearly identifiable pattern during the event periods. These findings suggest that BV-VPIN is the most accurate measure with the early-warning effect. We further demonstrate that our results on BV-VPIN metric are stable and robust under eight different volume classification schemes of time bars, bucket sizes and sample lengths.

Our second finding is that VPIN metric has a positive association with market volatility induced by toxic information flow. Our Pearson Correlation result shows that the prior level of VPIN has a correlation of 0.1174 with the current level of market risk, and 0.0872 with the current level of the absolute return. In addition, our conditional probability analysis shows two interesting patterns: 1) subsequent absolute returns are always low when there are low VPIN values. When the VPIN percentile is lower than 50%, absolute returns less than 0.5% take up 85 percentile of the distribution. As the VPIN percentile goes higher, the subsequent absolute returns are more dispersedly distributed. 2) VPIN anticipates a large proportion of extreme volatile events. When the absolute return percentiles is over 1.5%, the immediate preceding VPIN value is usually high, with most VPIN values exceeding 0.60. Our results from four multiple regression models further demonstrate that the prior level of VPIN has a significant positive correlation with the current level of market risk and absolute return. The positive relationship between VPIN and volatility is robust after we control for trade intensity and lag of volatility in the regression. Therefore, our results lend an out-of-sample support for the argument of Easley et al. (2012a) on the contentious debate of the effectiveness of VPIN.

The third and most important finding of our thesis is that there is a two-way interactive effect between VPIN and market liquidity. Specifically, in the VAR model of liquidity and VPIN, we find that the preceding change of all four high-frequency liquidity benchmarks has a positive effect on the current change of VPIN with significant coefficients of 0.011 to 0.036, where the preceding change of VPIN also has a positive effect on the current change of liquidity with significant coefficients of 0.025 to 0.044. The subsequent Granger Causality test shows evidence that market liquidity Granger causes the change of VPIN, which, in turn, has a positive feedback on the future change of the market liquidity. After adding volatility into the VAR model, we find that liquidity benchmarks have a positive association with market volatility, which is consistent with the fact that an increase in big-ask spreads leads to high volatility; Furthermore, the preceding change of VPIN is found to be positively associated with the current change of market volatility. Finally, we perform an impulse-response analysis on the relationship between VPIN and market liquidity. In the view of short-term effect, we find that given a shock of liquidity shortage, there is an immediate positive change on VPIN. In the view of long-term effect, we find that the impact on VPIN induced by the change of liquidity keeps a positive level to the fourth period with the highest impulse-response value of 0.03. This value declines gradually from the fourth to the sixth period, and remains stable from the seventh period onwards. More importantly, we also find a positive feedback effect on liquidity following an increase in VPIN. Specifically, in the view of short-term effect, VPIN makes an immediate impact on the change of liquidity at the end of the first period, but the magnitude of the impact is less than that from liquidity to VPIN. In the view of long-term effect, the feedback impact on liquidity induced by the change of VPIN monotonically increases till the mid of the second period, with the highest impulse-response value of 0.01. From the third to sixth period, the effect decreases gradually till stable.

To give an economic story as to the intrinsic game between informed traders and market makers, we take a specific view on the day of August 16, 2013 to illustrate how the two-way feedback effect applies to the Fat Finger Event. The unusually large purchase order submitted by the institutional traders (in the role of informed traders) of Everbright Securities created a huge order imbalance that shocked the market with an immediate increase in VPIN and volatility. As the traders discovered that the order was sent by mistake, they started to unwind positions. The unwinding of the massive positions by these traders leads them to seek liquidity. However, as market makers realized that the selling pressure is persistent, they start to withdraw, which in turn increase the concentration of toxic flow in the overall volume. Market makers noticed this phenomenon via the suddenly rising order imbalance and felt unsafe to stay at the current trading status, so they changed to a protected trading strategy by extending the bid-ask spread, which obviously led to a further shortage of market liquidity. This abnormal change on market liquidity had an evident effect on VPIN and kept VPIN at a high level, which made the market makers stay at a continuously cautious status. Hence, the vicious cycle was created, till market makers discovered that the informed trading disappeared and they began to provide liquidity again, then the VPIN values gradually dropped down to the normal range. Our thesis formalizes this story and presents empirical evidence using the VAR methodology and impulse-response analysis. Summarizing from our empirical research, we conclude that VPIN can be employed as an effective risk management tool and can be put in to practice in the prevalent high-frequency trading mechanism of the current financial world.

The remainder of this thesis is organized as follows. Section II reviews the literature about the proposition of VPIN estimation method, the research on VPIN and market volatility, and the benchmarks and proxies of previous liquidity research. Section III develops three testable hypotheses of this thesis. Section IV demonstrates the methodology, including the three metrics of VPIN metrics, research methods on market volatility prediction, and the high-frequency liquidity benchmarks and our models on market liquidity. Section V describes the institutional background, illustrates the sample data, provides descriptive statistics about three types of VPIN as well as volatility proxies and liquidity benchmarks, and demonstrates the robustness check of the Bulk Volume VPIN metric. Section VI shows our empirical results, including two event study analysis, tests of the association on VPIN and market volatility, and illustrations of the empirical findings on VPIN and high-frequency market liquidity. Section VII concludes the thesis.

II. Literature Review

Section 2 demonstrates the literature review of this paper. Abundant studies have been conducted on the assessment of informed trading. This thesis focuses on evaluating the effectiveness of VPIN while selecting the best trade classification algorithm for Chinese Stock Index Futures Market, predicting toxic-induced market volatility using the VPIN metric, and using high frequency liquidity benchmarks to test the relationship between VPIN and market liquidity. The review of relative literature is developed as follows. Section 2.1 presents studies of the high-frequency trading research background; Section 2.2 reviews the literature development on the research of informed trading, evolving from indirect measures to direct measures; Section 2.3 presents the key determinant on the calculation of different types of VPIN -- algorithms on differentiating buys and sells; Section 2.4 states the previous research on market volatility based on high frequency trading metric; and Section 2.5 reviews the benchmarks and proxies of previous liquidity research.

2.1 High Frequency Trading

The high frequency trading mechanism is gradually developed on the information-based market microstructure model introduced in "Market Microstructure Theory" from Maureen O'Hara (1995). Since the turn of the century, there has been a higher demand of market liquidity with an efficiency request of processing transaction data. Indeed, the rising HFT metric better suits current financial markets. The "Concept Release" of U.S. SEC (2010) states that HFT has already played a major role in current market. Compared to the traditional low-frequency trading metric, HFT has three evident advantages: HFT can avoid the psychologically irrational decision of investors such as greed or fright, as HFT realizes trading strategies through an electronic platform; HFT can make settlements in almost zero seconds, as deals are not made by investors manually but based on the price sequence automatically, which is doubtlessly more suitable for intraday trading and fairly important to face the speedy price changes in financial markets; the investors can apply different trading strategies in HFT metric and make the best choice due to different market status.

However, there comes a huge problem of risk management deficiency for highly volatile events in HFT mechanism. May 6, 2010 is a memorable day in the worldwide financial market for the sudden emergence of the U.S. Flash Crash Event. The E-mini S&P 500 futures fell 5.1% in the 13-min period of 2:32 to 2:45, while it rose 6.4% in the 23-min period of 2:46 to 3:08. Figure 1 shows the extremely intraday volatility in U.S. equity indices on May 6, 2010:

[Please insert Figure 1 about here]

It is generally accepted that this event was the result of a new trading paradigm emanating from legislative changes in ‘Regulation National Market System’ (2005). Two proceeding CFTC-SEC reports describe this liquidity crisis event, stating that the price was driven down because of the combined selling pressure from the sell algorithm, HFTs, and other traders. SEC Chairman Mary Schapiro made a summarized speech (2010) after the Flash Crash Event, appealing the market fairness with adapt to the rapid development of high frequency trading metric, and stating that the professional firms with the best accessibility to the financial markets should obey the obligations to support the stability of the markets.

2.2 Measurement of Informed Trading

Information plays a crucial role in the high frequency trading metric. Even in only a few minutes, the bid-ask spread made by high frequency market makers can be affected by the rolling information. As traders execute different trading strategies according to the information, their information-driven trading behaviour has influence on the stock price formation process with possible directions and the future order flow intensity (Hasbrouck, 1991). That is to say, whether different investors could receive the same level of information from the observed quote, namely the different private information events owned by investors, will have a huge impact on market stability (Easley, O'Hara, and Saar, 2001). Hence, the measurement of informed trading is the key to realizing the HFT metric. In essence, order flows carry information, and the information-based model is constructed to explore inner information asymmetry. Every time market makers and informed traders make a transaction, the information flows, passing from informed traders to market makers. Subsequently, the transactions release the information to more people via the bid-ask spread determined by information.

There are two stages from previous research about the measurement of informed trading, namely the indirect measurement, and the direct measurement. The earliest estimation of information asymmetry among order flows is the bid-ask spread. The larger the spread is, the higher the information asymmetry exists between market makers and investors. Later on, recent research literature figured out a quantitative measure method -- the probability of informed trading. The measurement of informed trading are introduced as follows.

2.2.1 Indirect Measure

Early literature shows indirect methods to measure informed trading. As information asymmetry cannot be observed from the market, researchers try to find substituted variables to measure the extent of information asymmetry.

The bid-ask spread is the first substituted measurement variable of informed trading. For example, Bagehot (1971), Copeland & Galai (1983) and Glosten & Milgrom (1985) use the bid-ask spread to test the extent of information asymmetry. Bagehot (1971) takes the bid-ask spread to explain the information risk faced by market makers. From his perspective, market exists because informed traders exploit the profit from uninformed traders. On the basis of bid-ask valuation models, Copeland & Galai (1983) show that more informed traders lead to a bigger bid-ask spread made by market makers for making up their potential loss. In other words, as the bid-ask spread increases with greater price volatility in assets, comparatively more bid-ask spread leads to a higher possibility in the existence of informed trading. Glosten & Milgrom (1985) further develop an alternative microstructure model that is often used to analyze trading and price formation, showing that compared to the returns of uninformed traders without the inside information, an overestimated return may be caused by the information-based bid-ask spread for informed traders.

Moreover, Benston & Hagerman (1974), Stoll (1978b), Easley & O'Hara (1987), Chiang & Venkatesh (1988), Hasbrouck (1991), and Sarin, Shastri & Shastri (2000) propose other substituted variables linked to the bid-ask spread in order to indirectly measure informed trading. Benston & Hagerman (1974) test the association of transaction cost to both systematic and unsystematic risk, and their results show that unsystematic risk is related to spread. Stoll (1978b) takes the data of NASDAQ stock market to make regression models on the spread to the trading volume, the price per share, and the variability of return. The results show that spreads are positively associated with the risk and negatively associated with price and volume, and the variability of return could be the proxy of information asymmetry. Easley & O'Hara (1987) investigate the effect of trade size on security prices, showing that trade size introduces an adverse selection problem in security trading. Chiang & Venkatesh (1988) examine the bid-ask spread, proving that insider holdings are positively related to the information costs of the dealers, and that the concentration of insider holdings could be the proxy of information asymmetry. Hasbrouck (1991) separates the variance of price movement into two parts according to whether it is relevant to trading price based on the vector auto-regression model, and regards the variance on the part of relevance to trading price as a substituted variable of the informed trading. Sarin, Shastri and Shastri (2000) find that higher insider ownership is associated with wider spreads, and the information asymmetry faced by traders has a positive association with the insider ownership.

However, all the substituted variables mentioned above cannot accurately reflect the information risk, and further studies are needed to make up the defect on the previous research using a specific quantitative angle.

2.2.2 Direct Measure

Recent literature displays direct methods to measure informed trading, which means that the description of informed trading is measured by specific possibility. Two of the most famous models to examine the probability of informed trading are the PIN model (Probability of Information-based Trading) and the VPIN model (Volume-Synchronized Probability of Informed Trading).

PIN is formally proposed by Easley, Kiefer, O'Hara, and Paperman (1996), and is also referred to as EKOP model. This measurement of the information asymmetry between informed and uninformed trades is built on the theoretical work of Easley and O’Hara (1992), in which they set up a sequential trade model of security price formation, focus on the information effect on prices, and analyze the effect of uncertainty information event to market behavior. The PIN model is indeed a start point for the research of asymmetric information from low-frequency to high-frequency. It is not directly observable, but based on a function of the theoretical parameters of a market microstructure model estimated by a numerical maximized likelihood function.

Abundant studies look at the analysis of information risk based on PIN model (Easley et al., 1997a & 1997b; Easley et al., 1998; Easley et al., 2001; Grammig et al., 2001; Nyholm, 2002; Easley et al., 2002; Barclay & Hendershot, 2003; Vega, 2006; Aslan et al., 2007; Lu & Wong, 2008). Easley, Kiefer, & O’Hara (1997a) study on the relationship between stock characteristics and information risks by taking trade size as the indicator. Their results do not show a significant relationship between the trade sizes to PIN. Easley, Kiefer, & O’Hara (1997b) propose a herding model. As the uninformed traders will mimic the actions of other investors and take actions conditioning on the immediately previous order event, they expand the potential order events of the original PIN model from 9 conditional branches to 27 branches. Easley, O’Hara, & Paperman (1998) investigate the information role of financial analysts, estimate PIN for a sample of NYSE stocks, and present that the coverage of financial analysts is not effective for testing the extent of the informed trading. Easley, O’Hara, & Saar (2001) study on the relationship between stock split and information risk. Their results show that after splitting, stock traders increase evidently, but this increase movement has a small effect on PIN, thus illustrating that stock splits do not reduce information asymmetries. Grammig, Schiereck, & Theissen (2001) analyze the association between the degree of trader anonymity and the probability of informed trading. Their results show that the anonymous trading system is preferred by the informed traders. They also demonstrate that the adverse selection component and the size of the spread have positive associations with PIN. Nyholm (2002) presents that the probability of information-based trading has a positive correlation with the observed quoted spreads on the basis of PIN model. Easley et al. (2002) propose the idea that PIN is associated to asset pricing, and document that higher PIN stocks have higher rates of return, representing higher volatility. Specifically, their results show that a ten percent difference in the PIN of two stocks will result in a difference of 250 basis points among the annually expected returns. Barclay & Hendershot (2003) examine the effect of different trade hours on the discovery of price. Their results demonstrate that the period around market opening has higher PINs, revealing more private information, while the period around market closing has lower PINs; Vega (2006) calculates the PIN prior to an earnings announcement. Results show that PIN is associated with the stock performance. Aslan, Easley, Hvidkjaer, & O'Hara (2007) do research on the relationship between several characteristics of company and information risk based on PIN model. Their results show that the company size, opening time, Tobin's Q, amount of financial analysts of a company have a negative relationship with information risk, while the proportion of inner stock holders and the turnover rate have a positive relationship with the information risk. Lu & Wong (2008) use PIN model to test the information risk of Taiwan stock market, and document that information risk is an evidently determinant factor of the stock return of Taiwan stock market. Their results also present that an increase of ten percentage point in PIN requires an additional of four to seven percent in annual stock returns.

However, there are a number of researches done with the proposed challenge to the effectiveness of PIN model. Their challenges mainly focus on three aspects.

First, the appropriateness of PIN in measuring information-based trading is a key discussion point. Venter & De Jongh (2006) use statistical methods to do research on PIN model. Their results show that in the actual trading data, orders of buying and selling are of positive correlation, while the correlation deducted from the model is negative, meaning the PIN model does not fit data very well. Aktas, Bodt, Declerck & Van Oppens (2007) provide a validity test on the behavior of PINs on a series of merger and acquisition corporate event announcements. Their results show that PIN decreases before the event period and increases after the release of the information. Thus they state that PIN is misleading as a proxy of informed trading. Benos & Jochec (2007) find similar problems. Using a large set of stocks, they find that PIN is lower in the periods before earning announcements dates than in the periods after. This finding shows inconsistent results with the predictable ability of PIN. Duarte & Young (2008) use a two-pass Fama-Macbeth regression to separate PIN into two components. Their results show that the part of PIN related to illiquidity is priced, but the part related to asymmetric information is not.

Second, several papers show that the PIN estimations could suffer biases for different reasons such as trade misclassification, the boundary solution or floating-point exception in active stocks. Boehmer, Grammig & Theissen (2007) show that misclassification of buy and sell directions could lead to a downward estimation of PIN, and the magnitude of bias is related to the trading intensity. Lin & Ke (2011) state that the floating-point exception, which might eliminate acceptable solutions to the parameters in the optimization of maximum likelihood estimation. Yan & Zhang (2012) report evidence that boundary solutions can lead to a bias in the estimation process of PIN.

Third, many researchers also demonstrate that PIN estimation is not significant to describe the effect of information risk to asset pricing, mainly with the query to the idea proposed by Easley et al. (2002). Hughes, Liu & Liu (2007) document that the reason of Easley et al. (2002) showing a positive correlation between information asymmetry and asset pricing based on PIN model is because their number of assets is finite. Therefore, the risk of information asymmetry cannot be dispersed. They state that in a large economic scale, information risk does not have an evident correlation with asset pricing. Kubota & Takehara (2009) measure the information risk of Japanese stock market based on PIN model. They use PIN as an additional explanatory variable to the Fama and French three-factor benchmark model, showing that the information risk is positively, but not evidently, related to the return of stock market.

Recent research has improved the original static PIN model to a time-varying VPIN model. The main change is based on the idea of Lei & Wu (2005) and Easley et al. (2008). Lei & Wu (2005) demonstrate a framework to investigate the time-varying interactions between the informed and the uninformed trading activities. They state that the time-varying probability of information-based trading is a suitable proxy for bid–ask spreads, and the time-varying characteristics adding into PIN acts a better effect of measurement on information asymmetry than the existing measurements. Easley et al. (2008) put the static frame of PIN into a dynamic GARCH model. The model could depict the characteristic of time-varying arrival rates of the informed and the uninformed trades, making the estimating frequency up to daily. This method shows the basic frame of the rolling-window VPIN model, with the motion of time is defined upon every same proportion of volume.

In order to overcome the flaw on the lag of parameter estimating at the request of a high frequency trading mechanism, as well as to seek the effectiveness in the risk measurement at the intraday level, Easley, Lopez and O'Hara (2011a) formally propose the concept of VPIN based on intraday transaction data. VPIN is in fact a variation and extension to the concept of PIN as a high-frequency estimate. From the analysis of Easley et al. (2011a), VPIN successfully signaled Flash Crash on May 6th with achieving its maximum level as early as several hours ahead of the event happens. This new approach introduces the information arrival process, makes the estimation match with updated information, and proposes a measure to the intraday information risk of the high frequency trading context.

The study of VPIN presents the impact of HFT on order flows. Easley et al. (2012a) introduce the concept of “order flow toxicity” to represent the adverse selection risk in HFT context. They state that the market makers might not be aware that they provide liquidity at a loss, and order flow is toxic when it has adverse selection on these market makers. To measure order flow toxicity, Easley et al. (2012a) impute order imbalances through a monotone function of the absolute price changes to gauge the probability of information-based trading on the basis of the volume imbalance and the trade intensity, and use the BV-VPIN metric to forecast the market volatility induced by toxicity. The inner algorithm is that market makers face the prospect of losses due to adverse selection when order flows become imbalanced. Hence, the estimates of time-varying toxicity level become a crucial factor in determining the participation of market makers. If they believe that toxicity is high, they will liquidate their positions and leave the market.

Some researchers have done validity research on VPIN, and document that VPIN is an effective indicator of market volatility. Bethel, Leinweber, Rübel, & Wu (2011) confirm that VPIN could have given a strong signal before the Flash Crash event on May 6^{th}, 2010, and view it as a contribution of a fully-fledged early risk warning system for unusual market conditions. Abad & Yagüe (2012) use 15 stocks from the Spanish market, revisit the VPIN estimation process and the three key variables, and test for the effectiveness of VPIN model. They conclude that VPIN is a straightforward way to measure the adverse selection risk and is well suited for the high frequency trading market.

However, criticisms are also proposed by recent researchers. Andersen and Bondarenko (2014a) show that the VPIN measure has no incremental predictive power for future volatility. Specifically, they state that TR-VPIN is not a good indicator of short-run volatility with a limited predictive power because it reached the highest value after the flash crash. The heart of Andersen and Bondarenko (2014) offers claims that order imbalance is flawed, because the classification algorithm is wrongly accepted. Easley et al. (2012d) claim protestation on the view of Andersen and Bondarenko (2014a), stating that their attack on their original paper (2012a) takes an incorrect analysis and draws an unjustified conclusion. In fact, the real dispute still focuses on the effectiveness of the trade classification algorithms that Easley has used in (2011c & 2012a), TR-VPIN and BV-VPIN, respectively.

Potential applications of the VPIN metric are suggested by Easley et al. (2011a, 2011b, 2012a). For execution brokers, VPIN is a benchmark for filling the orders of their customers and looking for the best time of execution; for investors, VPIN can also monitor their brokers' actions and decide the most adaptable trading strategies; for market regulators, VPIN is a risk management tool and warning indicator that can make market activity regulated under different flow toxicity levels. In Easley et al. (2011b), VPIN contract also can be used as a hedge tool rather than just as a risk management tool, against the higher levels of order toxicity.

2.3 Trade Classification Algorithms

The difference of trade classification methods, which differentiate buy orders and sell orders, is the key procedure for the calculation of VPIN, and also viewed as the key component to explore the theory of market microstructure. In the research of the trade classification algorithms, the tick rule, the quote rule, and the Lee-Ready rule are the main rules adopted in previous literature. In trading classification methods used in the estimation of the probability of informed trading, Easley et al. (2011a) relies on TR-VPIN with time bars, and Easley et al. (2012a, 2012b) adopts a bulk volume classification procedure (BV-VPIN) using a CDF transformation of absolute price changes. Easley et al. (2012a) also hold a theoretical comparison among three trade classification methods: TR (Tick Rule), LR (Lee-Ready Algorithm), and BV (Bulk Volume Classification). TR and BV are both level-1 algorithms, only using trade price data; while LR is a level-2 algorithm, using both trade and quote data.

Literatures on the research of trade classification are also abundant. (Hasbrouck, 1988, Lee & Ready, 1991, Ellis et al., 2000, Finucane et al., 2000, Chakrabarty et al., 2012, Easley et al., 2012b). Hasbrouck (1988) use the classification of trades as buys and sells to test the information asymmetry of the market. This study finds strong evidence that compared to small trades, large trades convey more information. Lee & Ready (1991) evaluate alternative methods for the classification of buy or sell orders, with the intraday trade and quote data. They propose Lee-Ready classification procedure to improve trade classification accuracy. Ellis et al. (2000) study the performance of distinct trade classification algorithms for the NASDAQ market, including the quote rule, the tick test, and the Lee-Ready rule. Their work summarizes the previous trade classification algorithms. Finucane et al. (2000) provide a more detailed analysis on the performance of the different trade classified forecasting methods. In their results, the accuracy of prediction algorithms, such as LR and TR, are influenced by trade size, spread and frequency of trades and quotes. In their results, LR and TR approach give very similar performance. Their research also shows that the spread will contribute in a positive way to the performance of the tick test. That is to say, the higher the spread, the higher the accuracy of this particular method on judgement of the trade sign. Chakrabarty, Pascual, & Shkilko (2012) compare the accuracy of Bulk Volume Classification (BVC) proposed by Easley et al. (2012a) to the traditional Tick Rule (TR) for a sample of equity trades executed on NASDAQ's INET platform (observed signed trades). Built according to the means of accuracy ratios, their results show that TR produces more accurate estimates of order imbalances and order flow toxicity, though BV-VPIN is comparatively more time-saving. They results have not shown whether BV classification is more stable; Easley et al. (2012b) make a horse race between Tick Rule (TR) and Bulk Volume Classification (BVC) methods. Their results show that TR is a useful identifier for the classification of the aggressor side of trading; BV is also an accurate classification method; but more importantly compared to TR, BV can explain the trading ranges for high-low prices, which will be useful for knowing the trading intentions from the market transactions.

2.4 Market Volatility

Since the 2010 Flash Crash Event, recent literature has shown continuous attention on the research of volatility in high frequency trading metric (Kirilenko et al., 2011; Madhavan, 2012; Hasbrouck & Saar, 2012). Kirilenko et al. (2011) use an E-Mini Dataset to examine trading in the E-Mini S&P 500 Futures. They summarize that HFTs did not lead to the Flash Crash, but their responses to the unusual market conditions, namely the huge selling pressure, exacerbated the highly volatile extent of the market. In other words, the large order imbalance caused by the automated execution program of selling futures contracts accelerated the price movement. Madhavan (2012) provides measures to gauge the fragmentation, and demonstrates the important factors on determining the extreme price movements. Their results state the linkage to higher frequency quotation activity and the current high levels of fragmentation, and displays a different point of view to the Flash Crash stemmed from an unlikely confluence of events as a result of the high volatile market. Hasbrouck & Saar (2012) use HFT metric to analyze the low-latency activity, and find that the increased low-latency activity improves short-term volatility.

In the research of VPIN, the volatility to be forecasted in VPIN metric is the short-term, toxicity-induced volatility. From the concept release on equity market structure of SEC (2010), primary concerns are proposed regarding short-term volatility on HFTs, especially the excessive short-term volatility. Prado (2012) states that there are three main characteristics should be illustrated on toxic-induced market volatility. First, this type of volatility is microstructural because it appears as a result of a failure in the liquidity provision process; second, the toxic-induced volatility is predictable because liquidity providers come under stress gradually; thirdly, the liquidity failure is typically short-termed as a price jump will attract position takers who will operate as tactical liquidity providers. There is an ongoing debate on the relationship between VPIN and market volatility (Easley et al., 2012; Yildiz et al., 2013; Andersen & Bondarenko, 2014). With the metric of BV-VPIN, Easley et al. (2012a) express a specifically all-round test on the research of toxic-induced volatility. They take the absolute return as the proxy for the market volatility and find VPIN and absolute return are positively correlated. With two different volatility measures, Yildiz et al. (2013) take an all-round analysis for the research on the characteristics of VPIN, demonstrating a positive association of VPIN and future volatility. Andersen and Bondarenko (2014) however state a contrary view that VPIN has no predictive ability for the future market volatility as it reached the highest value after the flash crash.

2.5 Market Liquidity

Liquidity is of paramount importance in the empirical asset pricing, market efficiency, and corporate finance. More liquidity allows a more efficient use of capital resources in the financial market. However, the unobservable nature of liquidity makes it difficult for a single measure to capture its various dimensions. Summarizing from previous literature, Table 1 lists the high-frequency liquidity benchmarks and the low-frequency liquidity proxies as follows:

[Please Insert Table 1 about here]

Abundant research has been done on the liquidity proxies in low-frequency market. Major contributions are made gradually by Roll (1984), Cooper et al. (1985), Lesmond et al. (1999), Amihud (2002), Pastor & Stambaugh (2002), Hasbrouck (2004), Holden (2009), and Goyenko et al. (2009). Roll (1984) reports the Roll estimator of liquidity. According to the serial covariance of the price change, he develops an estimator of the effective spread. Cooper et al. (1985) measure the price impact by the Amivest Liquidity ratio, which is the average of the volume to the absolute return in a specific time range. Lesmond et al. (1999) put forward another estimator of the effective spread named LOT Mixed measure. They also put forward the Zeros proxy, with the notion of the proportion of the days having zero returns. Amihud (2002) develops the famous Amihud measure of liquidity. It is an illiquidity measure of price impact representing the response of daily price related to one dollar of trading volume. Pastor & Stambaugh (2002) reports a Gamma measure of price impact, with the specific measurement of the order flow shock of the previous trading day. Hasbrouck (2004) demonstrates Gibbs method. It is a Bayesian estimation method of the Roll model. Holden (2009) extends the Roll measure by adding the notion of the idiosyncratic adjusted price change. Based on the thought that the observable price minimizes the negotiation costs between potential traders, Goyenko et al. (2009) and Holden (2009) develop the Effective Tick method. Goyenko et al. (2009) also post LOT Y-split method where the most parts are similar to the LOT Mixed, except that the region difference and the upper bond cap. Meanwhile, they develop an extended version of Zeros method, by calculating the ratio of the number of positive trading volume days having zero return to the sum of the number of trading and non-trading days in a specific period. They also extend Amihud proxy by testing the ratio of the percent cost proxy and the average daily currency volume.

Moving into the high-frequency trading era, there is a developing literature on the research of high-frequency liquidity. Goyenko et al. (2009) and Fong et al. (2011) summarizes the high-frequency spread benchmarks proposed in previous literature. Goyenko et al. (2009) take a view of three high-frequency liquidity benchmarks, including the effective spread from TAQ, effective spread from 605 Rule, and the realized spread. They also analyze three price impact benchmarks, including the static price impact, Lambda, and the 5-minute price impact. Fong et al. (2011) evaluate eight percent-cost low-frequency proxies on four percent-cost high-frequency benchmarks, namely percent the effective spread, the percent quoted spread, the percent realized spread, the and percent price impact. They also examine eleven cost-per-volume proxies relative to a cost-per-volume benchmark Lambda.

Multiple research states that HFT improves the provision of overall market liquidity (Jain, 2005; Chaboud et al, 2009; Hendershoot et al., 2011; Brogaard et al., 2014). Based on the announcement dates by the leading stock exchanges of 120 countries, Jain (2005) examines the automation impact on the market, and presents that the automated stock trading improves the liquidity provision and the informative spread of stock markets while lowering the cost of equity. Chaboud et al. (2009) study the effects between computerized trading in foreign exchange and get a positive result. Similarly, Hendershoot et al. (2011) test the association between algorithmic trading and market liquidity, and find that liquidity for the large stocks are enhanced due to the algorithmic trading. Brogaard et al. (2014) use level-1 data from NASDAQ, further proving that HFT is beneficial to price efficiency and liquidity provision, especially at high volatile times.

There are also researchers proving that high frequency trading causes losses to market liquidity (Cartea & Penalva, 2011; Jarrow & Protter, 2011). Based on the model of liquidity traders, market makers, and the HFT proxy, Cartea & Penalva (2011) displays that HFT increases the price volume and price volatility, while causes losses to market makers and liquidity traders. With a theoretical model assuming the frictionless and competitive market, Jarrow & Protter (2011) proposes similar conclusions that HFT may have a dysfunctional role in the market liquidity provision.

Easley et al. (2011c) notice the importance of market liquidity and present a possible explanation of the Flash Crash Event. They state that there exists an evaporation of liquidity in the marketplace during the event period. This severe liquidity mismatch is exacerbated by the withdrawal of liquidity from electronic market makers and the change on their trading strategies. Easley et al. (2012a) also present a possible explanation for the VPIN metric that high toxicity will cause losses to liquidity providers. Therefore, when facing high toxicity or namely high VPIN, liquidity providers may drop out of the market and cause the drain of liquidity.

III. Testable Hypotheses

Section 3 provides a detailed description of testable hypotheses for our empirical analysis. Andersen and Bondarenko (2014) propose three questions around the recent dispute of VPIN: whether VPIN reached an extremely high level before the beginning of the Flash Crash; whether the bulk volume metric is the most suitable trade classification procedure than tick-rule while applying to high-frequency data; and whether VPIN demonstrates a forecasting power for the short-run future volatility under the high frequency trading mechanism. Although these problems of dispute are still in discussion, the problems are still the main concentration of research on VPIN. Our hypotheses are established on the basis of these recent research disputes.

3.1 VPIN

H1: CDF lines of Bulk Volume VPIN have reached an extremely high level before the emergence of high volatility, and stay at a high level through the high volatile periods.

The difference of trade classification methods has been noted as the key procedure for the calculation of VPIN. Easley et al. (2011a) and Andersen & Bondarenko (2014) rely on the tick rule VPIN metric (TR-VPIN), while Abad & Yague (2012), Easley et al. (2012a), and Yildiz et al. (2013) adopt the bulk volume classification procedure (BV-VPIN).

Several studies have dealt with the predictive power of VPIN according to the choice of trade classification algorithm. Easley et al. (2012a) use the tick data of 2010 to 2011 and conclude that BV algorithm is superior to the tick-based algorithms in accuracy. They provide evidence that bulk volume classification is a good indicator of order flow imbalance in bars while the tick rule is not. However, oppositions are proposed by other empirical tests. Chakrabarty et al. (2012) compare tick rule and BVC based on order imbalance estimation and the detection of toxic events. They find that BVC is more successful in the classification of large and more frequently traded stocks in both bar types. But they get a different result from Easley et al. (2012a) that bulk tick rule is a better indicator of order imbalance, and state that VPIN estimates of bulk tick rule are better detector of toxic events than BVC values; Andersen & Bondarenko (2014a) show that the tick rule classification performs better than BVC with a sample of S&P 500 futures, and in (2014b) they continue to conclude that VPIN is not an appropriate measure to detect events like the Flash Crash; Poeppe et al. (2014) compare the effect of VPIN based on the tick rule and bulk volume metrics with one year trading data in 2012 Germany DAX stocks. Their results also demonstrate that VPIN calculated with tick rule signals the crash better than with bulk classification.

We predict that the Bulk Volume VPIN performs better than the traditional tick rule and Lee-Ready method. As the sign of the volume is necessary as its correlation to toxicity, our goal is to develop a method as a measure of order flow toxicity. Easley et al. (2012) state that in the high frequency trading settings, the itemized approaches are problematic compared to the aggregated trades for trade classifications. The key difference between the bulk classification and the traditional algorithms is that latter one signs each single trade as either a buy or a sell, while the bulk classification method signs an aggregated group of the volume as buys and the remainder as sells within a specific timeframe. The overall level of volume signals the presence of new information, which indicates that the toxicity arises from good news or bad news. Besides, aggregating trades on one side of the market in short time intervals into one observation minimize the potential noise that multiple trades may arise. Compared to the bulk volume method, tick rule and Lee-Ready algorithm is commonly used for the markets where it is not possible to distinguish the aggressor's side of the trade, and not suitable to the high-frequency trading metric.

We present this hypothesis for the importance of choosing a best metric for the following volatility and liquidity research on VPIN. As there is not a platform in the Chinese Stock Market like IMET that can provide researchers the actual signed buy-sell identifiers for each trade, we test this hypothesis through a comparative approach of actual VPIN forecasting effects. Taking an intraday event analysis and a trend event analysis of LR-VPIN, TR-VPIN and the newest BV-VPIN, we test whether bulk volume classification has the most accurate forecasting ability on a high-frequency trading market.

3.2 VPIN, Market Volatility, and High-Frequency Liquidity

H2: In the high-frequency trading market, VPIN has a positive association with toxic-induced market volatility, and there exists a feedback effect that liquidity Granger-causes VPIN while VPIN also has a positive feedback on liquidity.

Easley et al. (2012a) document that VPIN has a positive association with toxicity-induced volatility in U.S. market and act as a risk management tool for market making activity. Abad & Yague (2012) also display that VPIN can that forecast the future volatility in the Spanish market. However, Andersen & Bondarenko (2014) post opposite result on VPIN metric, stating that VPIN has no predictive power over the market and does not have a clear association with toxic-induced market volatility.

This hypothesis is presented as we would like to test for the validity for the use of VPIN metric in an out-of-sample market, in order to extract the intrinsic effect of the market itself. Therefore, in the research of VPIN and market volatility, we test the association between VPIN and market volatility in the Chinese market using the method of the Pearson Correlation to grasp an overall connection, and further setting conditional probability analysis and multiple regression analysis to fully conduct the association between VPIN and market volatility.

Liquidity is characterized by a high level of trading activity. It is a key component under the high-frequency trading mechanism. From previous literature, liquidity (illiquidity) is represented by transaction costs, which includes two major categories – the bid-ask spread and the price impact. Bid-Ask Spread is defined as the spread between the buying price and selling price for a specific asset at the same time. There are mainly three types of costs that market makers face for designing this spread to cover, namely the risk cost of inventory holding, the cost of order processing, and the cost of trading with more informed traders. Hence, the bid-ask spread has to be large enough to cover these costs, and at the same time, yield a reasonable profit to market makers on his investment. Price impact is created by an investor on the process of asset trading. The price is pushed up while buying a specific asset, and pushed down while selling it. The price impact exists because of two reasons. The first reason is that markets are not completely liquid. Imbalance between buys and sells can be created by a large trade, and the only way to resolve this imbalance is with a change of price. Liquidity deficiency leads to this set of price change, and when the liquidity gradually returns to the market, the price change will reverse to another direction. The second reason is the informational characteristics of the price impact. If there exists a large set of trade, it will attract other investors to step in the market as they are motivated by the new information that the trader shows in the market.

Several studies notice the importance of liquidity on the market under the high-frequency trading mechanism. Hautsch & Jeleskovic (2008) have found that liquidity is casual for future volatility but not vice versa; Huang & Wang (2009) conclude that the lack of liquidity has been blamed for exacerbating the consequences during severe market conditions. From their perspective, liquidity is not enough to accommodate the trades coming from the abnormal trading pressure, thus the liquidity-driven selling makes the prices shift dramatically; Cartea & Penalva (2011) displays that HFT increases the price volume and price volatility, while causes losses to market makers and liquidity traders; Jarrow & Protter (2011) proposes similar conclusions that HFT may have a dysfunctional role in the market liquidity provision; Kirilenko et al. (2014) infer that market makers are overwhelmed by a large liquidity imbalance.

With regard to the metric of VPIN, Easley et al. (2010) present that there exists an evaporation of liquidity in the marketplace during the flash crash period. This severe liquidity mismatch is exacerbated by the withdrawal of liquidity from electronic market makers, and by the uncertainty about the market data affecting the trading strategies of market participants. From their perspective, huge losses cause the liquidity providers to gradually stop trading. Hence, they propose a notion that if the toxicity reaches an extreme level, liquidity providers will change to liquidity consumers. Easley et al. (2012a) present a possible explanation for the VPIN metric that high toxicity will cause losses to liquidity providers. Therefore, when facing high toxicity, or namely high VPIN, liquidity providers may drop out of the market and decrease the liquidity.

However, to sum up from all theoretical deductions, the association between liquidity and VPIN has not been empirically tested in the existing literature. Motivated by recent literature on informed trading and high-frequency liquidity, we present this hypothesis to contribute for the gap in present literature on empirically testing the feedback effect on VPIN and market liquidity. The origin of our thought is from the two high volatile events from China as the unusual liquidity provision is the major explanation for the future high volatility. When informed traders trigger an unusual liquidity fluctuation in the market, market makers will change their trading strategies by widening up the bid-ask spreads. Such market making behaviors rise up the measure of informed trading such as VPIN, and in turn refrain market makers from providing further liquidity to the market. Therefore, we conjecture a two-way feedback effect between VPIN and high-frequency liquidity as follows. On one hand, if there exists informed trading in the market, VPIN will rise as a result of liquidity deficiency; on the other hand, as VPIN rises to a high level, it will have a positive feedback effect on liquidity and make it decrease even further. To empirically shed lights on this issue, we take four high-frequency liquidity benchmarks including three spread benchmarks and one price impact benchmarks for the representation of market illiquidity, and employ the Vector Auto-Regression (VAR) model with impulse-response analysis to examine the intrinsic relationship of VPIN and market liquidity. This innovation point of our research on VPIN and liquidity is a major contribution from our thesis, as we extend the previous research by seeking further of the intrinsic reason on how VPIN works in the HFT market, test whether there exist associations between VPIN and liquidity, and present the whole story between informed traders and market makers in this high-frequency trading market with regard to the connection of VPIN, market volatility and liquidity.

IV. Methodology

Section 4 explains our methodologies, which are based on the PIN model and the VPIN model. Section 4.1 introduces the construction of VPIN model. Section 4.2 expresses the research methods on VPIN and market volatility prediction, including the Pearson correlation analysis, the conditional probability tendency analysis, and multiple regression analysis. Section 4.3 demonstrates the setting of vector auto-regression (VAR) model, the inner mechanism of Granger causality test, and the metric of impulse response analysis for our further research.

4.1 VPIN

The sequential trading diagram of 1996 PIN model is demonstrated in Figure 2, and the specific framework of PIN model is attached in Appendix A. Recent researchers change PIN model to the VPIN metric as there is a growing debate on the appropriateness of PIN in measuring information-based trading. The major problem is when adapting PIN model into high frequency trading markets, MLE could have the problem of convergence. Several papers also show that the PIN estimations could suffer several biases for different reasons such as trade misclassification, boundary solutions or the floating-point exception, especially in very active stocks.

[Please insert Figure 2 about here]

Both PIN and VPIN models require trading volume classified as buys or sells, with the notion that order imbalances signal the presence of adverse selection risk.

However, the VPIN approach has some practical advantages over the PIN methodology that make it particularly attractive for both investors and researchers. The main advantage is that VPIN does not require the estimation of non-observable parameters using optimization or numerical methods, thereby avoiding all the associated computational problems and biases. In addition, VPIN allows the capturing of risk variations at intraday level while the original PIN model does not. VPIN paradigm is “event-based time”. The transformation of dividing the session in equal volume buckets removes most intra-session seasonal effects. For example, high frequency market makers may target to turn their portfolio every fixed number of contracts traded (volume bucket) regardless of the chronological time. In fact, working in volume time presents significant statistical advantages.

As we mentioned before, with the hysteretic characteristics of estimated parameters, PIN cannot have the effective predictability in the context of high frequency intraday data. Researchers have explored methods for the wider application. The most progressive extension from to PIN model applying into a high frequency trading mechanism is stated in Easley et al. (2008). They extend the model of Easley and O’Hara (1992) to allow the arrival rates of informed and uninformed trades to be time-varying and forecasting, and change the static frame of EKOP (1996) PIN model into a dynamic microstructure GARCH model. The new model that they have proposed can describe time-varying arrival rates of informed and uninformed trades, make the estimating frequency up to daily, and have more adaptability to high frequency trading markets.

VPIN estimation model is built on the framework of the PIN estimation model. Easley et al. (2008) provide the fundamental basis for the proposition of VPIN.

For getting the sample of volume, first we uniformly separate the trading sequence into different groups, with each group noticed as a "volume bucket", V.

$$V = V_\tau^B + V_\tau^S$$

V_τ^B is the volume traded against the Ask, and V_τ^S is the volume traded against the Bid. We will discuss how to classify buy trades and sell trades in the following sections. According to Easley et al. (2008), for a particular period of time, the expected trade imbalance approximates the numerator of the PIN model, and the expected total number of trades equals the denominator of PIN. Specifically, the arrival rate of informed orders is:

$$E[|V_\tau^S - V_\tau^B|] \approx \alpha\mu$$

Because one volume bucket can be regarded as the aggregation of the volume from the up event, the volume from the down event, and the volume from no event happening. The arrival rate of all orders is:

$$\frac{1}{n}\sum_{t=1}^{n}(V_\tau^B + V_\tau^S) = V = \alpha(1-\delta)(\varepsilon + \mu + \varepsilon) +$$

$$\alpha\delta(\mu + \varepsilon + \varepsilon) + (1-\delta)(\varepsilon + \varepsilon) = \alpha\mu + 2\varepsilon$$

Hence, in the last step, VPIN can be calculated as:

$$VPIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} = \frac{\alpha\mu}{V} \approx \frac{\sum_{\tau=1}^{n} |V_\tau^S - V_\tau^B|}{nV}$$

From the above formula, VPIN is estimated by choosing appropriate V, which is the volume of each bucket, and n, which is the number of buckets, measuring trading imbalance and the extent on trading intensity. Easley et al. (2012a) state that VPIN is a more effective tool to measure the order flow toxicity in the high frequency trading world.

4.1.1 BV-VPIN Metric

One important thing is that we separate each transaction into a buy or a sell while we settle the volume bucket, because the direction of trading has inner connection with toxicity of order flow. Thus, considering factors of both the direction and the amount of volume, we could get the possibility for the existence of new information. If more information comes from buying, then it indicates that the toxicity comes from good information, vice versa. We estimate VPIN through the intensity and imbalance of observing buys and sells.

Knowing the metric transition from PIN to VPIN, we have to decide the key procedure that leads to the difference type of VPIN model – different algorithms of trading direction classification. There are three main algorithms from the research literature that we introduced in Section 2, namely Bulk Volume Classification, Tick Rule, and Lee-Ready Algorithm. In this section, we firstly introduce the newest proposed metric -- BV-VPIN. BV-VPIN metric is proposed by Easley et al. (2012a). They use a 4-step method to calculate VPIN with bulk volume classification method, which is a level-1 classification algorithm, with 3 key variables in the process of VPIN calculation.

Starting from three necessary elements -- time period of the trade, the corresponding price and the corresponding volume, the first step is to constitute time bars. Easley et al. (2012a) states that the aggregation of data will show a better vision of buys and sells, then will show better results of proceeding estimation. The reason of taking every trade into the sum of units is because there are noises in the correlation of trading goals and trading data, with the noises coming from the trading goal could be divided into small parts, thus will minimize its effect on the market.

Therefore, one order could arise many executions, which might disorder the calculation process. This opinion leads to the first key variable of the whole process – Bar Size. In Easley et al. (2012a), they use 1-min time bar, thus for each minute, they consider the change of price and the aggregated volume of all the trades in the bar. So the original sample is expanded to a combination of one-unit trades with the price change and volume aggregation of bars.

Next step is to assign volume buckets and to apply bulk volume classification algorithm. The second key variable of VPIN calculation process is Volume Bucket, because the homogeneous information that will be necessary to compute the order imbalance in the following step is contained in the volume buckets. In Easley et al. (2012a), they use 50 buckets to compute the VBS (volume bucket size). Hence, we divide the average daily volume by 50 and get the VBS. If the volume of a last trading is higher than necessary of the bucket, the exceeding part of volume will be transferred to the next bucket. Thus, a volume bucket can be seen as the aggregation of certain time bars, with some of the time bars need to fill one or more volume buckets. After assigning volume buckets, we come to the core of the process -- Bulk Volume Classification Algorithm. We classify the buy volume in the way of multiplying the normal distribution evaluated in the standardized change of price $Z(\Delta P/\sigma_P)$ by the assigned volume bar. In the same way, we classify the sell volume in the way of multiplying the complementary of normal distribution evaluated in the standardized change of price $1 - Z(\Delta P/\sigma_P)$ by the assigned volume bar. In this way,

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot Z(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}})$$

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot \left[1 - Z(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}})\right] = V - V_\tau^B$$

From the above formula, $t(\tau)$ is the last time bar index of the τth volume bucket; Z is the CDF of the normal distribution; $\sigma_{\Delta P}$ is the standard deviation of price changes between time bars. Thus, buys and sells are split, in order to calculate the order imbalance. This is the essence of Bulk Volume VPIN calculation.

The third step is to compute order imbalance (OI). Each OI is the absolute difference between buy volume and sell volume in each time bars. And lastly, through the computation of order imbalance, we can obtain BV-VPIN values with the third key variable referred to: the sample length, which is represented by n. In Easley et al. (2012a), they use a sample length of 50 to compute VPIN.

Following Easley et al. (2008),

$$VPIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_b + \varepsilon_s} \approx \frac{E[|V_\tau^S - V_\tau^B|]}{E[V_\tau^S + V_\tau^B]} = \frac{\sum_{\tau=1}^{n} OI_\tau}{n \times VBS}$$

Hence, VPIN is the average of order imbalances with respect to the sample length. We get an observation number of VPIN according to the rolling-window procedure of the buckets. For example, the first VPIN is calculated from bucket #1 to bucket #50. Hence, if bucket #51 is filled, the second VPIN is calculated from bucket #2 to bucket #51. The sample length can be changed according to the specific analysis. Taking the number of buckets is 50 as a benchmark, a sample length of 50 means a daily VPIN, while a sample length of 250 means a five-day VPIN. A corresponding illustration example is in Section 4, stating the 4-step BV-VPIN calculation using a small example from the data of Chinese Stock Index Futures Market.

4.1.2 TR-VPIN Metric

The main feature of the volume-synchronized method is to classify all trades in each one-minute time bar (could be alternative) as buy-initiated or sell-initiated. Section 4.1.1 has introduced the classification algorithm of bulk volume. In Section 4.1.2 and Section 4.1.3, we present two other famous trade classification algorithms, Tick Rule and Lee-Ready, respectively. We focus on 1-min time bar because it is less noisy and easier for processing. Tick rule algotirhm is originated from Holthausen, Leftwich and Mayers (1987). The popular level-1 classification rule defines a trade as buyer-initiated or seller-initiated according to the following rules:

If the current trade price is higher than the preceding trade price, this trade is defined as an uptick trade, meaning the trade is buyer-initiated; If the current trade price is lower than the preceding trade price, this trade is defined as a downtick trade, meaning the trade is seller-initiated; If the current trade price is the same as the preceding trade price, this trade is defined as a zero tick trade. In this situation, tick rule looks for the closest prior price which has been signed to buys or sells, thus classified the trade as buyer-initiated or seller-initiated, respectively.

Knowing the details of Tick Rule classification, we apply this algorithm into VPIN estimation model. TR-VPIN is calculated through four steps as BV-VPIN. The difference between TR-VPIN and BV-VPIN model is only the adopted classification algorithm.

4.1.3 LR-VPIN Metric

In this subsection, we still focus on classifying trades according to 1-min time bar as buys and sells, but with the adoption of Lee-Ready classification algorithm. Unlike bulk volume method and tick rule method, Lee-Ready rule is a level-2 classification rule, which needs both the trade and the quote data. Lee-Ready Algorithm is formally proposed by Lee & Ready (1991) for classifying a trade as buyer-initiated or seller-initiated according to the following rules:

We consider the median of the best bid quote and the best ask quote as a benchmark. If the current trade price is higher than the benchmark, this trade is defined as a uptick trade, meaning the trade is buyer-initiated; If the current trade price is lower than the benchmark, this trade is defined as a downtick trade, meaning the trade is seller-initiated; If the current trade price is the same as the benchmark, this trade is defined as a zero tick trade. In this situation, tick rule is led in, looking for the closet prior price which has been signed to buys or sells, thus classified the trade as buyer-initiated or seller-initiated, respectively.

Knowing the details of Lee-Ready classification, we apply this algorithm into VPIN estimation model. LR-VPIN is calculated through four steps as BV-VPIN. The difference between LR-VPIN, TR-VPIN and BV-VPIN model is only the adopted classification algorithm.

4.2 VPIN and Market Volatility

The research on market volatility prediction could be viewed as the research to future price movements. However, the standard microstructure model is not well-suited in the high frequency world, as it is hard to capture the market behavior of liquidity supply and volatile motion in microseconds; besides, under the high frequency metric, the econometrics knowledge for building a model of liquidity and volatility is not abundant. From the previous introduction, we know that market makers will leave the market due to the potential losses and cause liquidity reduction and price variability. Hence, we present research on VPIN metric and market volatility prediction from two views. Section 4.2.1 looks at the association between VPIN and market volatility via Pearson Correlation Coefficient. Section 4.2.2 presents the conditional probability tendency analysis of VPIN and market volatility. Section 4.2.3 constructs multiple regression models to test the association between VPIN and market volatility.

4.2.1 Pearson Correlation Analysis

We first concentrate on the research of the association between the volatility and price movements over subsequent volume bucket. In this section, we focus on the VPIN metric and the future price movements. Specifically, we take a view of Pearson correlation between VPIN and market volatility. Two volatility proxies are included in our research. Following Yildiz et al. (2013), we take the market risk as the first proxy for the market volatility. The risk is the standard deviation of returns in the volume bucket τ based on dividing the volume bucket into ten equal sub-volume buckets. Following Easley et al. (2012a), we take the absolute return as the second proxy for market volatility. The absolute price return over the following bucket is calculated by $\left|\frac{P_\tau}{P_{\tau-1}} - 1\right|$. Taking the thought of Easley et al. (2012a), we use a time bar of 1 min, a volume bucket size of 50, and a sample length of 250 as a combination to estimate VPIN. VPINs can be estimated using various combinations of the number of volume buckets per day and the sample length. We try to find a basic connection between VPIN and these two market volatility proxies through the Pearson Correlation Analysis.

4.2.2 Conditional Probability Analysis

Taking a deeper view, we then concentrate on the conditional probabilities, namely the probability distributions of VPIN metric and the absolute returns. We focus on the issue of the subsequent behavior of absolute returns when VPIN is high, and the issue of the preceding level of VPIN when absolute returns are high.

Following Easley et al. (2012a), we group VPIN values in 5%-tiles and absolute returns in bins of size 0.25% so that we can display discrete distributions, then we compute the joint distribution:

$$\left(VPIN_{\tau-1}, \left|\frac{P_\tau}{P_{\tau-1}} - 1\right|\right)$$

From this joint distribution we derive two conditional probability distributions. For predicting toxicity-induced volatility, what matters is whether the level of VPIN at any time is unusual relative to its distribution for the asset in question. We first examine the distribution of absolute returns over the subsequent volume bucket conditional on VPIN being in each of our twenty 5%-tile bins. In other words, we show the distributions of returns at time τ given VPIN at time τ-1. In this realm, we try to know whether prior VPIN can have an effect on market volatility.

$$Prob\left(\left|\frac{P_\tau}{P_{\tau-1}} - 1\right| |VPIN_{\tau-1}\right)$$

Next, we examine the distribution of *VPIN* in bucket τ-1 conditioning on absolute returns between buckets τ-1 and τ. In other words, we show the distributions of VPIN at time τ-1 given returns at time τ. In this realm, we try to discover the preceding level of VPIN with respect to a high volatility.

$$Prob\left(VPIN_{\tau-1}|\left|\frac{P_\tau}{P_{\tau-1}}-1\right|\right)$$

4.2.3 Multiple Regression Analysis

In this section, following the thought of Yildiz et al. (2013), we further set up four multiple regression models on VPIN and market volatility:

Model 1:

$$Volatility_\tau = c + \alpha_1 VPIN_{\tau-1} + \varepsilon_t$$

Model 2:

$$Volatility_\tau = c + \alpha_1 VPIN_{\tau-1} + \alpha_2 Volatility_{\tau-1} + \varepsilon_t$$

Model 3:

$$Volatility_\tau = c + \alpha_1 VPIN_{\tau-1} + \alpha_2 TI_{\tau-1} + \varepsilon_t$$

Model 4:

$$Volatility_\tau = c + \alpha_1 VPIN_{\tau-1} + \alpha_2 Volatility_{\tau-1} + \alpha_3 TI_{\tau-1} + \varepsilon_t$$

We take the prior level of trading intensity (TI) and the lag of volatility as the control variables, using the market risk and the absolute return as the proxy of market volatility, and taking the trade size as the proxy for the trade intensity. The two control variables are proposed by Easley et al. (2012a) and Yildiz et al. (2013) as the determinant factors of the VPIN measurement. Easlely et al. (2012a) present that trade intensity affect the willingness of liquidity suppliers to provide liquidity, therefore, it acts as a determinant factor when examining VPIN as a measure of order flow toxicity; Yildiz et al. (2013) also use the trade intensity as determinant factor of VPIN, but they theoretically take the lag of volatility as another control variable in their regression on

VPIN and market volatility, and try to study another situation other than the pure result from VPIN and order imbalance.

Based on the analysis from Pearson Correlation Coefficients, as well as the conditional probabilities showing the tendency on the change of VPIN, we examine four multiple regression models in order to seek quantitatively whether there is a significant association between VPIN and market volatility. Model 1 tests the individual predicting power of VPIN. Model 2 takes the lag of volatility into evaluation while Model 3 controls for lagged trade intensity. Model 4 considers both of the two control variables into evaluation.

4.3 VPIN and Market Liquidity

Our research of VPIN and high-frequency liquidity is divided into three parts. In section 4.3.1, we introduce Vector Auto-Regression (VAR) model; in section 4.3.2, we use Granger causality test for the association exploration of VPIN and market liquidity; in section 4.3.3, we lead in the impulse response analysis to further demonstrate this association.

4.3.1 Vector Auto-Regression Model

The Vector Auto-Regression model is one of the most successful models for the analysis of multiple time series. The VAR model is an extension version for the research of multiple time series compared to the univariate auto-regression model. Because VAR models represent the correlations among a set of variables, they are often used to analyze certain aspects of the relationships between the variables of interest. It is proven to be especially useful to describe the dynamic behavior of financial time series and forecast the economic phenomenon.

We start with a unit root test on VPIN and high-frequency liquidity benchmarks, examining whether time series are stationary. Taking the existence of a unit root as the null hypothesis, we use ADF test (Augmented Dickey–Fuller test) for the examination of our time series. It is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. Eviews shows a strong rejection on the null hypothesis of non-stationary in all series with a significant p-value at 1% level, which documents that all the time series are trend stationary. After passing the unit root test, we set up the first Vector Auto-Regression Model of VPIN and high-frequency liquidity as follows:

$$\begin{pmatrix} \Delta Liquidity_t \\ \Delta VPIN_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{pmatrix} \begin{pmatrix} \Delta Liquidity_{t-1} \\ \Delta VPIN_{t-1} \end{pmatrix}$$

$$+ \begin{pmatrix} \phi_{11,2} & \phi_{12,2} \\ \phi_{21,2} & \phi_{22,2} \end{pmatrix} \begin{pmatrix} \Delta Liquidity_{t-2} \\ \Delta VPIN_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$$

One notion here is that VAR can be estimated equation by equation by OLS regression and that these estimations of the short-run parameters are consistent when the dynamic is correctly identified. We choose the best lag length of 2 referring to the minimum value of Akaike Information Criterion (AIC) and Schwartz Criterion (SC). ε_t is an (n*1) unobservable zero-mean white noise vector process (serially uncorrelated) of the unobservable variable. The model above identifies the lead-lag relationship between the changing quantities of VPIN and high-frequency liquidity. It tests whether changes in liquidity lead to changes in VPIN, and vice versa. Two other coefficients for us are more important among all. We also set up a second VAR model for our all-round test connecting to the market volatility. Model is expressed as follows:

$$\begin{pmatrix} \Delta Volatility_t \\ \Delta Liquidity_t \\ \Delta VPIN_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} + \begin{pmatrix} \phi_{11,1} & \phi_{12,1} & \phi_{13,1} \\ \phi_{21,1} & \phi_{22,1} & \phi_{23,1} \\ \phi_{31,1} & \phi_{32,1} & \phi_{33,1} \end{pmatrix} \begin{pmatrix} \Delta Volatility_{t-1} \\ \Delta Liquidity_{t-1} \\ \Delta VPIN_{t-1} \end{pmatrix}$$

$$+ \begin{pmatrix} \phi_{11,2} & \phi_{12,2} & \phi_{13,2} \\ \phi_{21,2} & \phi_{22,2} & \phi_{23,2} \\ \phi_{31,2} & \phi_{32,2} & \phi_{33,2} \end{pmatrix} \begin{pmatrix} \Delta Volatility_{t-2} \\ \Delta Liquidity_{t-2} \\ \Delta VPIN_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}$$

We choose the best lag length of 2 referring to the minimum value of Akaike Information Criterion (AIC) and Schwartz Criterion (SC). The model above identifies the lead-lag relationship between the VPIN and high-frequency liquidity. It tests whether changes in liquidity lead to changes in VPIN, and vice versa. Two of the coefficients for us are more important among all. $\phi_{12,1}$ stands for the coefficient of $\Delta Liquidity_{t-1}$ to $\Delta Volatility_t$; $\phi_{13,1}$ stands for the coefficient of $\Delta VPIN_{t-1}$ to $\Delta Volatility_t$. We would like to explore a full view of the association among high-frequency liquidity, VPIN, and market volatility through the analysis of VAR model.

4.3.2 Granger Causality Test

Multiple Granger causality analysis is usually performed by fitting a vector auto-regressive model (VAR) to the time series. The intuition is inspired by the thought of Granger (1969). It is an important forecasting type of structural analysis with regard to the dynamic properties of VAR model. The main notion is that if a variable or groups of variables is found to have the explanation power to another variable or group variables, then the former variable is defined to Granger cause the latter variable. One important note is that Granger causality test is only explainable for the forecasting ability. We first employ the Granger causality test on the first VAR model based for the research of VPIN and high-frequency liquidity, then employ

Granger test on the second model for the research of liquidity, VPIN and volatility. We aim to find the feedback effect on VPIN and market liquidity.

4.3.3 Impulse Response Analysis

Impulse response analysis is another important type of structural analysis on the basis of the vector auto-regression model. In the field of signal processing, the impulse response of a dynamic system is its impulse output when presented with an input signal. Generally speaking, an impulse response refers to the reaction of any dynamic system in response to external change, and the impulse response function is to consider the effect on the change of the stochastic error term passing from one variable to another. In our research, considering our first VAR model of liquidity and VPIN as an example:

$$\Delta Liquidity_t = \alpha_1 + \phi_{11,1}\Delta Liquidity_{t-1} + \phi_{12,1}\Delta VPIN_{t-1} + \phi_{11,2}\Delta Liquidity_{t-2} + \phi_{12,2}\Delta VPIN_{t-2} + \varepsilon_{1,t}$$

$$\Delta VPIN_t = \alpha_2 + \phi_{21,1}\Delta Liquidity_{t-1} + \phi_{22,1}\Delta VPIN_{t-1} + \phi_{21,2}\Delta Liquidity_{t-2} + \phi_{22,2}\Delta VPIN_{t-2} + \varepsilon_{2,t}$$

Assuming ε_t is independent, we take two cases as examples for the interpretation of the impulse response analysis. If $\varepsilon_{1,t}$ equals to 1 and $\varepsilon_{2,t}$ equals to 0 at the time t, it is reckoned that the current change of liquidity (illiquidity) is given an impulse, and this impulse leads to the change of VPIN; On the contrary, if $\varepsilon_{1,t}$ equals to 0 and $\varepsilon_{2,t}$ equals to 1 at the time t, the current change of VPIN is thought to receive an impulse, and this impulse leads to the change of liquidity. The impulse responses are zero if one of the variables does not Granger-cause the other variables taken as a group. Hence, based on the result of Granger causality test, we go further to analysis the input effect to both the intensity and the time period on the changes of liquidity and VPIN, and take a deeper thinking of the economic story.

V. Sample Data and Descriptive Statistics

Section 5 introduces the sample data and basic descriptive statistics. Section 5.1 shows the institutional background of the research. Section 5.2 illustrates our sample data. Section 5.3 shows the descriptive statistics of VPIN metrics, market volatility proxies, and high-frequency liquidity benchmarks. Section 5.4 displays the robustness check of VPIN metric, testing the stability under different volume classification schemes.

5.1 Institutional Background

The Chinese capital market is currently in a transition from a planned economy to a market economy (Aharony et al., 2000; Chen et al., 2008). There are two main reasons for us to choose Chinese Stock Index Futures data in our research. One is the suitable characteristics of the emerging market for our liquidity research, and the second is the adaptability of VPIN with respect to the nature of the Chinese market.

Firstly, the Chinese market is of significant influence in the worldwide financial market, with its systematic properties and trading mechanisms quite different in comparison to U.S. market. Table 2 shows the best emerging markets worldwide and China comes on the top of the list. Measured by bid-ask spread, the liquidity characteristics in the Shanghai Stock Market are the best among all the emerging markets due to a large amount of competitive buy and sell orders, which keep the spread at a relatively low level. This indicates that the electronic trading mechanism adapts to the specific environment, with higher efficiency and lower cost. Research on the Chinese market can provide us with an out-of-sample test for the validity of VPIN, and can shed new lights on the debate about the usefulness of VPIN. This is part of our reason to use Chinese market rather than other economies.

[Please insert Table 2 about here]

Secondly, China's stock market is known for its speculative and manipulative nature, which leads to a high degree of information asymmetry between institutional investors and retail investors (FT, 2011; Bloomberg, 2012). In the mid of transition from the planned economy to a market economy, the corporate governance of China is in a peculiar position (Garcia et al., 2009). Due to a relatively high administration intervention and a weak protection of property rights, China’s legal system constitutions, including investor protection systems, corporate governance, accounting standards, and quality of government, are significantly less developed (LLPS, 2004; Allen et al., 2005; Jian & Wang, 2010; Bo et al., 2011). Allen et al. (2005) make a specific comparison the country-level research, and show the creditor rights and shareholder protection among China and 49 sample countries from LLSV (1998). They also gather data from top international rating agencies, and make a comparison of legal systems across different countries in contrast to China by examining their efficiency of the judicial system, rule of law, corruption, anti-director rights, creditor rights, and accounting standards. Overall evidence suggests that China has lower creditor and shareholder protection than the majority of LLSV sample countries, and has a very low development speed of legal systems. Besides, because there is a lack of independent and professional auditors, the current status of Chinese accounting system is counterproductive to China’s current infrastructure. Since the auditor legal liability is not well defined, China has not yet formed its first complete set of generally accepted accounting principles (Aharony et al., 2000; Allen et al., 2005). In this emerging market, material changes are usually not disclosed according to the business conditions of corporations, and published statements are not always prepared by International Accounting Standards (IAS). Thus, given the fact that China has relatively poor disclosure rules and auditing adaptability, incompact judicial systems and ineffective law enforcement, with a lack of codes to protect investors, Chinese markets are still in a situation of multiple embezzled frauds and high information asymmetry (Chakravarty et al., 1998; Yang, 2003; Chan et al., 2008). Specifically, compared to the rich disclosure environment of US firms, both the quality and quantity of the accounting disclosures in Chinese capital markets are relatively low (Zhou, 2007). In summary, the apparent lack of transparency in financial disclosure has drawn attentions among investors and researchers, and has displayed an urgent motivation of market research. VPIN should be more effective and pronounced to capture information asymmetry in this market. This is a more important reason for us to use the Chinese market on our research.

Therefore, we conduct an out-of-sample test for the validity of VPIN, in order to provide new evidence on the current debate with regard to the effectiveness of VPIN, as well as to choose the best VPIN metric for our liquidity research. The uniqueness of our data plays an important role in the contribution to the VPIN research, due to its speculative and manipulative nature of the Chinese market compared to the U.S. market. Informed trading and the magnitude of liquidity events should be more pronounced in such a market. If VPIN is indeed an effective measure of high-frequency informed trading, we should observe that VPIN exhibits a strong pattern of information toxicity with respect to our high-frequency liquidity measures.

5.2 Data Illustration

Our data is collected from the China Shanghai Stock Exchange. The sample is a 2-year 500 microseconds tick data of Chinese Stock Index Futures[1] from January 2012 to December 2013. In order to better concentrate on the main motions of the futures contracts, we shift out only the front-month futures contracts for every trading month during the two-year sample period. In order to eliminate the potential intraday effect, we extract the transaction logs before 9:30 and after 15:00 every trading day of the transaction period. All the data shifting and processing is executed through SAS software.

5.3 Descriptive Statistics

In this section we provide descriptive statistics for our empirical research. Section 5.3.1 shows the statistics of the three VPIN metrics that we have constructed. Section 5.3.2 displays the statistics of the two proxies of market volatility. Section 5.3.3 demonstrates the statistics for the four high-frequency liquidity benchmarks.

5.3.1 VPIN Metrics

We extend the previous research by adding the Lee-Ready level-2 trade classification algorithm into the evaluation, and hold a comparative study of three methods for the computation of VPIN. The three major trade classification algorithms are the Lee-Ready Classification (LR, 1991), Tick Rule Classification (TR, 1987), and Bulk Volume Classification (BV, 2012). For these three algorithms, we test

[1] China Shanghai Shenzhen 300 Stock Index Futures are traded in China Financial Futures Exchange. The first trading day is April 16, 2010. It takes 'T+0' trading rule. Final settlement day of each contract is the third Friday of the contract month, which is the changing day of the main futures contract.

whether CDFs of VPIN have clearly reached a high level prior to the occurrence of high volatile events; namely, which VPIN metric has the most accurate predictive effect. We calculate all three VPIN models through SAS software with the four steps introduced in our methodology -- establish the transaction sequence, define volume buckets and the trading algorithm, compute order imbalances, and finally get the value of VPIN. In this section, we use BV-VPIN on the day Aug 16, 2013 as an example to show the explicit steps to calculate VPIN by our sample. TR-VPIN and LR-VPIN also follow the four step procedure, with the only difference in the buy-sell classification algorithm. The first step is the process of defining time bars. Table 3 shows a sample of transaction data in the Chinese Stock Index Futures Market on Aug 16, 2013.

[Please insert Table 3 about here]

Table 4 shows the computation of time bars in our small sample used in Table 1. From 9:31 to 9:36, five 1-min bars are calculated from the small sample. TB volume is the sum volume of all transactions in the corresponding minute, and TB Price Change means the last transaction price in the corresponding minute deducts the last transaction price in the previous minute. Hence, the small sample can be considered to be expanded. For example, from 9:31 to 9:32, we can consider 2002 independent trades with each unit of trade holding a price change of -1.6, instead of considering one transaction with a volume of 2002.

[Please insert Table 4 about here]

The second step is the process of assigning volume buckets and applying the bulk volume classification algorithm. Table 5 explains how we define a volume bucket. The ADV (average daily volume) for Chinese Stock Index Futures from the year 2012 to 2013 is 462,400 shares. Following Easley et al. (2012a), here we use 50 buckets and obtain a VBS (volume bucket size) of 9248 shares. We take an excerpt from 9:31 to 9:32 with a total volume of 2033. Taking consideration at the first part of 233 shares, we can see that if this part is added to the Bucket #18167, the total VBS (9204) will be fulfilled. Thus, the rest of that minute is assigned to the next bucket (Bucket #18168). Then follows the accumulated process, and the buckets are filled one by one. With the process of bucket completion, buy volume and sell volume are calculated through the multiplication of each volume bar and the normal distribution evaluated by the standardized price change from the buy part and the sell part. We have introduced the classification methodology of the BV-VPIN model in Section 4.

[Please insert Table 5 about here]

The third step is the process of getting the order imbalance. Table 6 shows the order imbalance for the first six buckets on Aug 16, 2013. The time for the accumulation of buckets differs.

[Please insert Table 6 about here]

The last step is the process of VPIN calculation with respect to the sample length. Table 7 shows the first ten results of VPIN calculation for Aug 16, 2013, with a sample length of 50 buckets (Following Easley et al., 2012a). For example, for the first VPIN, the initial bucket is Bucket #1, while the final bucket is Bucket #50; for the second VPIN, the initial bucket is Bucket #2, while the final bucket is Bucket #51.

[Please insert Table 7 about here]

Table 8 reports basic statistics on the three algorithms of BV-VPIN from 2012 to 2013. Taking BV-VPIN values (1-50-50) as a benchmark, we can get the contrasted VPIN values while estimating the validity of VPIN values in alternative markets. In our research to the Chinese market, we show a mean value of 0.2961 with a standard deviation of 0.0861 on VPIN calculation; in the research of Easley et al. (2012a) on the U.S. market, they show a result of 0.2251; while in the research of Abad & Yague (2012) on the Spanish market, their result is 0.2268. There are two possible reasons to interpret the fact that Chinese VPIN values are higher than US and Spanish: the first reason is that the information asymmetry is more severe than US and European markets; and the second possible reason is that the size of Chinese companies are relatively medium and small compared to U.S. and European, and the toxicity problem is usually more severe in low volume stocks than medium volume and high volume stocks (Yildiz et al., 2013). The asymmetric information risk is higher for the more illiquid and less frequently traded stocks due to the fact that proportionally there are fewer uninformed traders, which increases the probability of trading with an informed trader (Abad & Yague, 2012). Hence, the higher VPIN is possibly due to a group of relatively small companies.

[Please insert Table 8 about here]

The above illustrations show the explicit calculation steps of VPIN values. In this section we also show the three categories of VPIN, calculated by three different algorithms -- the Lee-Ready Rule, Tick Rule, and Bulk Volume Classification. Figures 3(a), 4(a), 5(a) show the VPIN series calculated by three different algorithms of Chinese Stock Index Futures Market -- BV-VPIN, TR-VPIN, LR-VPIN, respectively. The period is two years, from January 1, 2012 to December 31, 2013. We adopt 1-min time bars, use 50 buckets to compute the VBS, and take 50 buckets as sample length (1-50-50). Figures 3(b), 4(b), 5(b) show the corresponding historical distribution of each series of VPIN calculation. BV-VPIN gets an accumulated VPIN percentage of 50% when the VPIN value is around 0.3, 80% when VPIN value is 0.39, and reach to the peak percentage when VPIN values are above 0.5. TR-VPIN gets an accumulated VPIN percentage of 50% when VPIN value is around 0.13, 80% when VPIN value is 0.17, and reach to the peak percentage when VPIN values are above 0.24. LR-VPIN gets an accumulated VPIN percentage of 50% when VPIN value is around 0.09, 80% when VPIN value is 0.11, and reach to the peak percentage when VPIN values are above 0.18.

[Please insert Figure 3(a) - 3(b) about here]

[Please insert Figure 4(a) - 4(b) about here]

[Please insert Figure 5(a) - 5(b) about here]

Obviously, we can see that in August, 2013 and June, 2013, there are higher VPIN values appearing in each metric. These results correspond to the high volatility events of China -- ‘Fat Finger Event’ in August, 2013, and ‘Money Shortage’ in June, 2013. We will use these two events to further discuss the issue whether VPIN has the predictive ability, and make a comparison on the effect of the above three algorithms.

5.3.2 Market Volatility Proxies

Table 9 provides the basic descriptive statistics of the market volatility proxies. Two proxies of the market volatility are shown in the table, namely the absolute return and the risk. The absolute return is the absolute value of returns in each volume bucket, and the market risk is calculated after dividing each volume bucket into ten sub volume buckets with getting the standard deviation of returns in each volume bucket. The absolute return has a mean of 0.00119 and a standard deviation of 0.00113, while the market risk has a mean of 0.00091 and a standard deviation of 0.00061. With these two stable market volatility proxies, we formalize the proxy values by multiplying 1000 to meet the scale of VPIN for further analysis.

[Please insert Table 9 about here]

5.3.3 High Frequency Liquidity Benchmarks

[Please insert Table 10 about here]

In our thesis, we focus on high-frequency liquidity measures that are more suitable to examine their association with VPIN. Our research uses four different benchmarks as representatives for the high frequency liquidity research at a specific time interval, namely the Effective Spread, the Realized Spread, the Quoted Spread, and the Price Impact. These benchmarks are determined by market liquidity, and the most liquid or widely traded securities tend to have the narrowest spreads. That is to say, if there is a significant lower liquidity, the bid-ask spread will expand substantially. Hence, the high frequency benchmarks are in fact directly showing the illiquidity degree of the market. Introductions and calculation procedures for these benchmarks are shown in Appendix B. Table 10 displays the descriptive statistics of the four high-frequency liquidity benchmarks. The mean values of the four benchmarks are 0.00011, 0.00602, 0.00011, and 0.00602, respectively. According to the descriptive statistics, all the benchmarks are stable enough to support our latter analysis, and we formalize the benchmarks by multiplying 1000 to meet the scale of VPIN for further analysis.

VI. Empirical Results

Section 6 demonstrates our empirical analysis and results. Section 6.1 shows the results of two event studies on the forecasting ability of VPIN. Section 6.2 displays the results regarding the association of VPIN and market volatility. Section 6.3 provides our findings on VPIN and market liquidity in the high-frequency market.

6.1 Forecasting Ability of VPIN

This section serves the results for our first hypothesis, testing whether CDFs of Bulk Volume VPIN have reached an extremely high level before high volatile periods, and keep staying at a high level till the end of the periods. We concentrate on two influential high-volatile events in Chinese Stock Index Futures Market: 'Fat Finger Event' on August 16, 2013 and 'Money Shortage' in June, 2013. With the three types of VPIN metric -- BV-VPIN, TR-VPIN and LR-VPIN, Section 6.1.1 and Section 6.1.2 show the intraday forecasting effect and the trend forecasting effect according to these two events, respectively.

6.1.1 Fat Finger Event

"Fat Finger Event" happened on August 16, 2013, which was incurred by institutional traders from China Everbright Securities who mistakenly submitted billions of purchase orders for index future shares. At 11:05 am, there was a huge rise of 5% on Chinese Stock Index Futures market in one minute, and kept rising till midday. From 2 pm, a huge plunge happened. Figure 6(a) shows that the CDF lines of BV-VPIN kept rising from 10:09 a.m., crossed the threshold of 0.8 about 15 minutes ahead of the huge price rise of 5.62% at 11:05 a.m., and stayed at high level through the huge plunge in the afternoon, which documents that toxicity has already increased and stayed at the high level. Because the CDFs of VPIN has already increased to an extremely high level before the high volatile period happens and stayed at a high level during the severe volatile time, BV-VPIN does have the early-warning effect statistically. However, TR-VPIN and LR-VPIN do not show a stable predictive effectiveness of this intraday event. In Figure 6 (b), the CDF line of TR-VPIN suddenly rises to an extremely high value above 0.9 around 11:02 am, which just leaves a very short time before the high volatile event happens. Moreover, several minutes before the time of high rise, there is a plunge tendency showing in the CDF line, which is misleading to some extent. Hence in this case, TR-VPIN has a little predictive effect but not exceeds the ability of BV-VPIN. In Figure 6 (c), the CDF line of LR-VPIN on the contrary shows a decline tendency before the high volatile of the stock price, and it raises to the extreme level afterwards around 11:08 a.m. later than the high volatile event happens, which shows this metric does not have a clear predictive power of the price movements.

[Please insert Figure 6(a) - 6(c) about here]

6.1.2 Money Shortage Event

"Money Shortage Event" also had a dramatic effect on the Chinese market, causing several times of market fluctuations during two transaction weeks of June 2013. The money shortage occurred when the benchmark money market rates of China shot up in June 2013, as the People's Bank of China declined to extend bank credits, suddenly causing a liquidity shortage shock in the entire market. On June 24, 2013, Chinese Stock Index Futures Market plunged 7.1% from 2296 to 2133. On June 25, 2013, the trend of plunge continued, till the historical minimum 1996 points. For the comparative analysis of the three algorithms, we first take a specific look from June 24 to June 25, then analyze a 2-week period from June 17 to June 28 to see the general trend of VPIN series which are the two days of highest volatility. Our results show that BV-VPIN demonstrates a stable tendency attaining an uncommonly high level prior to each high volatile time, while TR-VPIN and LR-VPIN still do not show a stable effect that have clear predictive function of this trend event.

Figure 7(a) and 7(b) shows the trend of BV-VPIN in the two periods. In Figure 7(a), the CDF of VPIN has already risen and stayed over 0.9 at an extremely high level at 10 a.m. before the huge plunge beginning in the afternoon of June 24, and stay at the level till the end of the high volatile price movements on June 25. Figure 7(b) clearly shows CDFs percentile of VPIN at an extremely high level around the high volatile events, which demonstrates the adaptability of BV-VPIN to the price movement. Figure 8(a) and 8(b) shows the trend of TR-VPIN in the two periods. In Figure 8(a), the CDF of TR-VPIN fluctuates around a normal level of 0.5 during the volatile days and rises to a comparatively high level over 0.8 several minutes after the plunge happens. Figure 8(b) also does not clearly show an extremely high CDF of VPIN around the high volatile time. Figure 9(a) and 9(b) shows the trend of LR-VPIN in the two periods. In Figure 9(a), LR-VPIN stays at the high level of VPIN values over 0.9 around several cases of high volatile time, but from the case of the huge plunge happens on June 24, LR-VPINs declines to a level below 0.3, which obviously do not have the ability of predicting the price movements. Figure 9(b) does not show a stably high level of LR-VPIN during the high volatile events from the afternoon of June 24. This result does not indicate an accumulated high market toxicity level.

[Please insert Figure 7(a) - 7(b) about here]

[Please insert Figure 8(a) - 8(b) about here]

[Please insert Figure 9(a) - 9(b) about here]

To sum up, we conclude that BV-VPIN is most accurate in predictive ability of the stock market than TR-VPIN and LR-VPIN. Specifically, we note the bulk volume classification method is more suitable for the high-frequency market than the bulk tick method. The fact that LR algorithm appears weaker is probably because there are multiple trades and quotes for the same reported time period.

6.1.3 Robustness Check of BV-VPIN

In order to test whether BV-VPIN metric is stable enough for market prediction as well as for our following research on market volatility and liquidity, we hold robustness check of BV-VPIN under different volume classification schemes. We test eight different combinations of time bars, bucket sizes and sample lengths, which are the three key variables for the VPIN calculation. Following the two VPIN series from the original model of Easley et al. (2012a), we first display the combination of 1-min time bars, 50 buckets to compute VBS and 50 buckets as the sample length, and the combination of 5-min time bars, 50 buckets to compute VBS and 50 buckets as the sample length. The expressions of these two combinations are VPIN 1-50-50 and VPIN 5-50-50, respectively. Then we compute two VPIN series in order to assess the effect of changes in the sample length by changing the previous sample length to 250, namely combinations of VPIN 1-50-250 and VPIN 5-50-250. We also construct four additional VPIN series. Specifically, in 1-min and 5-min time bars we take 1 bucket to compute VBS instead of 50 buckets stating previously for a proxy effect of a daily order imbalance. And regarding to the change of sample length, we take 5 buckets for the proxy of a weekly VPIN and 20 buckets for the proxy of a monthly VPIN. Thus the four additional series are namely VPIN 1-1-5, VPIN 5-1-5, VPIN 1-1-20, and VPIN 5-1-20. Within these eight series, we take an all-round view of checking whether VPIN metrics are stable by using different values of the three key variables.

[Please insert Table 11 about here]

[Please insert Figure 10(a) – 10(h) about here]

Table 11 expresses the statistics of our robustness check procedure. This table contains eight combinations of the three key VPIN calculation variables -- time bar, VBS, and sample length. All the mean values and the range values are in a normal scale compared to the research literature of other countries (Abad & Yague, 2012; Easley et al., 2012a), and the standard deviation is very small regardless to the change of daily, weekly or monthly VPIN effect that we construct for the test. The values of VPINs decline significantly when the size of the time bar is reduced, with the mean value of 5-50-50 VPIN of 0.3962 and 1-50-50 VPIN of 0.2961, as well as with the mean value of 5-1-5 VPIN of 0.1071 and 1-1-5 VPIN of 0.0617. The change of sample lengths does not evidently affect the values, with the mean value of 5-50-50

VPIN of 0.3942 and 5-50-250 VPIN of 0.3879, as well as with the mean value of 1-1-5 VPIN of 0.0617 and 1-1-20 VPIN of 0.0543.

We analyze the effect of the eight VPIN schemes over the graphs plotted in Figure 10 (a) to Figure 10 (h). Making a comparison among the above figures, we can clearly see the 8 curves expressing a similar tendency, with the only difference the intensity and range of the curves. In our two-year sample, VPIN gets the highest values on August 16, 2013 and in June 2013, which correspond perfectly to the two periods of high volatile events in the Chinese Stock Index Futures market. We also take a specific look with the two events of each schemes, and our results of all eight schemes demonstrate that the CDFs of VPIN rise before the crash and stay at the high level throughout the high volatile period.

Hence, based on the above analysis, we conclude that the change of time bars, buckets to compute the VBS, and buckets as the sample length do not have repercussion on the predictability of VPIN metric. Our results on BV-VPIN metric are therefore stable and robust under eight different volume classification schemes of time bars, bucket sizes and sample lengths.

6.2 VPIN and Market Volatility

This section serves the results for our second hypothesis, testing whether VPIN has a positive association with market volatility induced by toxic information flow. Table 12 presents correlation statistics of BV-VPIN and market volatility proxies. Two proxies of market volatility are the market risk and the absolute return. The coefficients shows that the prior level of VPIN has a positive correlation of 0.1174 with the current level of market risk, and 0.0872 with the current level of the absolute return, which indicates that the prior level of VPIN are positive correlated with the current level of market volatility. The coefficients between the prior level of VPIN and two volatility measures are strongly significant at 1% level.

[Please insert Table 12 about here]

We then present the conditional probability tendency analysis on the distribution of VPIN and the market volatility. Table 13(a) first examines the distribution of absolute returns over the subsequent volume bucket conditional on VPIN in each of the twenty 5-percentile bins. Twenty conditional distributions are set up, representing a distribution of the absolute returns conditioned on the prior level of VPIN. From Table 13(a), we can get the result that the subsequent absolute return are always low when there are low VPIN values. Taking a look at the VPIN percentiles of lower than 50%, absolute returns less than 0.5% take up 85 percentile of the distribution, while as the VPIN percentiles goes higher, the subsequent absolute returns are more disperse distributed and result in a relatively higher volatility. Compare from the case of 50% percentiles with VPIN percentiles of 90%, the absolute returns which are less than 0.5% drop from 85 percentile to 77 percentile, and obviously we get more cases of higher absolute return. Hence, the prior level of VPIN can have an effect on market volatility. Table 13(b) examines the distribution of VPIN in the prior bucket conditioning on the absolute returns between the prior and current bucket. Each column provides the distribution of prior VPINs conditional on the bin of size on the absolute returns at an interval of 0.25%. Taking a look at the absolute return percentiles over 1.50%, we find that the immediate preceding VPIN value is comparatively high in which 90% of VPIN exceed 60 percentile of the distribution. Hence, the preceding VPIN are usually high when the absolute returns are relatively large. This fact suggests that VPIN has some insurance functional value against extreme price volatility, and indicates that VPIN anticipates a large proportion of extreme volatile events.

[Please insert Table 13(a) and 13(b) about here]

Multiple regression models are set up in order to seek for an accurate association between VPIN and market volatility. The results are shown in Table 14. Table 14(a) demonstrates correlation coefficients of multiple regression models of market risk and VPIN. The lagged VPIN, the lagged market risk, and the lagged trade intensity all have a strong association at 1% significance level with the market risk. Table 14(b) displays correlation coefficients of multiple regression models of absolute return and VPIN. The lagged VPIN, the lagged absolute return, and the lagged trade intensity all have a strong association at 1% significance level with the absolute return. Table 14(c) shows the multiple regression analysis of four models. Panel A presents four models using the market risk as the proxy of market volatility. Result from the Model 1 states that the individual predictive effect of the prior level of VPIN on the current level of market risk is evidently positive, with a coefficient of 0.0831 at 1% significance level. Model 2 controls for the lagged market risk and shows a coefficient between prior level of VPIN and current level of market volatility of 0.0832 at 1% significance level. Model 3 controls for the lagged trade intensity and shows a coefficient between prior level of VPIN and current level of market risk of 0.0809 at 1%

significance level. Model 4 takes the lag of volatility and the prior level of trade intensity into evaluation. The coefficient of prior level of VPIN and the current level of market risk is 0.0794 at 1% significance level, still showing a strongly positive association. Panel B presents four models using the absolute return as the proxy of market volatility. The coefficients between the prior level of VPIN and current level of volatility for the four models are 0.1157, 0.1001, 0.1365, and 0.1270, respectively. All coefficients are significant at 1% level. Therefore, the positive relationship between VPIN and volatility is robust after we control for trade intensity and lag of volatility in our regression analysis, and our results provide an out-of-sample support for the argument of Easley et al. (2012a) in the current debate on the effectiveness of VPIN.

[Please insert Table 14 (a), 14 (b), and 14 (c) about here]

6.3 VPIN and Market Liquidity

This section serves the results for our third hypothesis, testing the interaction relationship between VPIN and high-frequency liquidity. We start the test on VPIN and market liquidity with constructions of Vector Auto-Regression model. Our first VAR model is constituted by two factors -- market liquidity and VPIN, with the liquidity represented by four high-frequency liquidity benchmarks. Before setting up the model, we have passed the unit root test indicating that the series are stable. We choose the lag length of 2 according to Akaike Information Criterion (AIC) and Schwarz Criterion (SC). Table 15 displays the coefficients of the model. The variables are formalized to meet the scale of VPIN. We find that the preceding change of all four high-frequency liquidity benchmarks has a positive effect on the current change of VPIN with significant coefficients of around 0.011 to 0.036, where the preceding change of VPIN also has a positive effect on the current change of liquidity with significant coefficients of 0.025 to 0.044. Taking the realized spread liquidity benchmark as an example, the VAR model with coefficients can be expressed as follows, with decomposition into two linear regression models:

[Please insert Table 15 about here]

$$\Delta Liquidity_t = \underset{(44.85)}{2.102} + \underset{(18.17)}{0.124\Delta Liquidity_{t-1}} + \underset{(4.762)}{0.025\Delta VPIN_{t-1}} + \underset{(20.58)}{0.139\Delta Liquidity_{t-2}} + \underset{(1.696)}{0.009\Delta VPIN_{t-2}} + \varepsilon_{1,t}$$

$$\Delta VPIN_t = \underset{(62.49)}{3.864} + \underset{(4.016)}{0.036\Delta Liquidity_{t-1}} + \underset{(16.36)}{0.112\Delta VPIN_{t-1}} + \underset{(5.379)}{0.048\Delta Liquidity_{t-2}} + \underset{(8.123)}{0.055\Delta VPIN_{t-2}} + \varepsilon_{2,t}$$

We notice from the above result that the preceding status of liquidity (illiquidity) has a positive effect on the current status of VPIN with a 1%-significant coefficient of 0.036; while the preceding VPIN status also has a feedback effect on liquidity with a 1%-significant coefficient of 0.025. This result indicates that the prior change of liquidity leads to the change of VPIN, as well as the prior change of VPIN also leads to the change of liquidity. We examine the result by Granger causality test based on the vector auto-regression model. Table 16 presents the results from Granger Causality tests for four high-frequency liquidity benchmarks. Two important results are presented from this table. First, among the four high-frequency liquidity benchmarks in the study on the Granger test of liquidity to VPIN, all the four statistics are strongly significant at 1% level. Second, in the study on the Granger test of VPIN to liquidity, all the four statistics, still, are strongly significant at 1% level. The results of the Granger Causality test shows evidence that market liquidity Granger causes the change of VPIN, and in turn has a positive feedback on the future change of the market liquidity. This innovative finding demonstrates a feedback effect between VPIN and liquidity. Therefore, when informed trading happens, VPIN rises as a result of liquidity decline; however, high values of VPIN draws a more protective strategy of market makers and thus making a more severe situation of liquidity insufficiency.

[Please insert Table 16 about here]

Link to our previous research on market volatility, we seek to consider the whole cause-effect mechanism of VPIN applying to financial market. We constitute our second VAR model, which is a three-factor model including volatility, liquidity and VPIN. The market volatility is represented by the absolute return. We still choose the lag length of 2 according to Akaike Information Criterion (AIC) and Schwarz Criterion (SC). The variables are formalized to meet the scale of VPIN. Taking the realized spread liquidity benchmark as an example, Table 17 displays the coefficients of the VAR model with the result expressed as follows:

[Please insert Table 17 about here]

$$\Delta Volatility_t = \underset{(28.46)}{0.448} + \underset{(51.51)}{0.366\Delta Volatility_{t-1}} + \underset{(25.76)}{0.059\Delta Liquidity_{t-1}}$$

$$+ \underset{(6.367)}{0.011\Delta VPIN_{t-1}} - \underset{(-11.87)}{0.082\Delta Volatility_{t-2}} + \underset{(5.240)}{0.012\Delta Liquidity_{t-2}}$$

$$- \underset{(-0.599)}{0.001\Delta VPIN_{t-2}} + \varepsilon_{1,t}$$

$$\Delta Liquidity_t = \underset{(42.29)}{2.038} - \underset{(-0.167)}{0.004\Delta Volatility_{t-1}} + \underset{(17.26)}{0.122\Delta Liquidity_{t-1}}$$

$$+ \underset{(4.660)}{0.024\Delta VPIN_{t-1}} + \underset{(5.653)}{0.011\Delta Volatility_{t-2}} + \underset{(17.79)}{0.128\Delta Liquidity_{t-2}}$$

$$+ \underset{(1.398)}{0.007\Delta VPIN_{t-2}} + \varepsilon_{2,t}$$

$$\Delta VPIN_t = \underset{(60.21)}{3.830} + \underset{(0.581)}{0.017\Delta Volatility_{t-1}} + \underset{(3.604)}{0.034\Delta Liquidity_{t-1}}$$

$$+ \underset{(16.289)}{0.112\Delta VPIN_{t-1}} + \underset{(1.819)}{0.051\Delta Volatility_{t-2}} + \underset{(4.383)}{0.042\Delta Liquidity_{t-2}}$$

$$+ \underset{(7.983)}{0.055\Delta VPIN_{t-2}} + \varepsilon_{3,t}$$

Similar to the results of previous model, we still find a significantly positive association between the prior status of liquidity (illiquidity) and the current change of VPIN with a 1%-significant coefficient of 0.034, and a positive association between the prior change of VPIN and the current change of liquidity with a coefficient of 0.024 at 1% significance level. This result indicates that the prior change of liquidity leads to the change of VPIN, as well as the prior change of VPIN also leads to the change of liquidity. Moreover, we also find a significant positive association of 0.011 between the preceding change of VPIN and current change of market volatility, and a significant positive association of 0.059 between the preceding change of liquidity and current change of market volatility. We also examine the result by Granger causality test based on the vector auto-regression model. Table 18 presents the results of four high frequency liquidity benchmarks from Granger Causality tests for market volatility, the liquidity benchmarks, and VPIN. Panel A shows the results for the Granger causality association between liquidity and VPIN. Similar to the result of our first VAR model, we get almost all the two-way statistics significant at 1% level, with only the effective spread to VPIN significant at 5% level. This result indicates that prior change of liquidity Granger causes VPIN while VPIN also has a feedback effect on liquidity. Panel B shows the results for the Granger causality association between VPIN and volatility. Suiting to the finding in our previous study of VPIN and volatility, all the four analysis reject the hypothesis that VPIN does not Granger cause volatility at the significant level of 1%. This result shows that VPIN has a positive correlation with market volatility, with a further proof of Granger causality relationship significant from VPIN to market volatility. Panel C shows the results for the Granger causality association between liquidity and volatility. Results show that all the two-way coefficients significant at 1% level. This finding indicates that liquidity benchmarks has a positive association with market volatility, which is consistent with the fact that a large bid-ask spread leads to a potential high volatility, as well as a feedback influence from the volatility to liquidity.

[Please insert Table 18 (a), (b), (c), and (d) about here]

Furthermore, we perform an impulse-response analysis on the basis of the VAR model. The impulse response analysis is for the purpose of testing an influence on one factor giving a shock impact by another factor. We aim to know the realized effect on high-frequency liquidity and VPIN metric. Figure 11 (a) and 11 (b) takes the realized spread as the high-frequency liquidity benchmark as a proxy for market illiquidity to demonstrate the result of impulse response analysis. 10 periods are chosen for this test as a result of examining with continuity. Figure 11(a) shows the impulse-response analysis of VPIN given by shocks of liquidity. Specifically, in the view of short-term effect, we find that given a shock of liquidity shortage, there is an immediate positive change on VPIN. In the view of long-term effect, we find that the impact on VPIN induced by the change of liquidity keeps a positive level to the fourth period with the highest impulse-response value of 0.03. This value declines gradually from the fourth to the sixth period, and remains stable from the seventh period onwards. More importantly, we also find a positive feedback effect on liquidity following an increase in VPIN. Figure 11(b) shows the impulse response analysis of liquidity given by shocks of VPIN. Specifically, in the view of short-term effect, VPIN makes an immediate impact on the change of liquidity at the end of the first period, but the magnitude of the impact is less than that from liquidity to VPIN. In the view of long-term effect, the feedback impact on liquidity induced by the change of VPIN monotonically increases till the mid of the second period, with the highest impulse-response value of 0.01. From the third to sixth period, the effect decreases gradually till stable.

[Please insert Figure 11 (a) and 11 (b) about here]

Taking the Fat Finger Event on Chinese Stock Index Futures Market as an example, we can take a further step on the interpretation of the events by this interesting discovery. We take a specific view on the impulse response analysis of the day August 16, 2013 for demonstration the two-way effect applying to explain the game between informed traders and market makers. Figure 12 (a) and 12 (b) takes the realized spread as the high-frequency liquidity benchmark as a proxy for market illiquidity to demonstrate the result of the intraday impulse response analysis. Still, 10 periods are chosen for this test as a result of examining with continuity. Figure 12(a) shows the impulse response analysis of VPIN given by shocks of liquidity. We can see that given a shock by the lack of liquidity, there is a positive change on VPIN. Specifically, in the view of short-term effect, illiquidity has an immediate positive impact on the change of VPIN at the first period; in the view of long-term effect, the impact on VPIN given by the decline of liquidity has increased till the third period, with the highest impulse response value of 0.97. From the third to the sixth period the impact declines, and gets stable from the seventh period. Figure 12(b) shows the impulse response analysis of liquidity given by shocks of VPIN. We can see that given an impact by the VPIN, there is a feedback effect on liquidity with a declination. In the view of short-term effect, VPIN has a positive impact on the change of liquidity (illiquidity) at the end of the first period, but much lesser than the impact from liquidity to VPIN with the highest impulse response value of 0.26 at the first period; in the view of long-term effect, the shock on liquidity given by the change of VPIN has been stable all along from the third period. Taking a comparative view with the intraday analysis and the whole sample analysis, we can see a similar tendency with the results of impulse response analysis, which shows a further proof for our findings on the two-way relationship between liquidity and VPIN.

[Please insert Figure 12 (a) and 12 (b) about here]

An economic story as to the intrinsic game between informed traders and market makers can be viewed from the Fat Finger Event. The unusually large purchase order submitted by the institutional traders (in the role of informed traders) of Everbright Securities created a huge order imbalance that shocked the market with an immediate increase in VPIN and volatility. As the traders discovered that the order was sent by mistake, they started to unwind positions. The unwinding of the massive positions by these traders leads them to seek liquidity. However, as market makers realized that the selling pressure is persistent, they start to withdraw, which in turn increase the concentration of toxic flow in the overall volume. Market makers noticed this phenomenon via the suddenly rising order imbalance and felt unsafe to stay at the current trading status, so they changed to a protected trading strategy by extending the bid-ask spread, which obviously led to a further shortage of market liquidity. This abnormal change on market liquidity had an evident effect on VPIN and kept VPIN at a high level, which made the market makers stay at a continuously cautious status. Hence, the vicious cycle was created, till market makers discovered that the informed trading disappeared and they began to provide liquidity again, then the VPIN values gradually dropped down to the normal range.

VII. Conclusion

With a more volatile condition of worldwide financial markets under the high frequency trading mechanism, there is an urging need for the market to have a better risk management system with regard to the fairness request. The research on VPIN starts a preliminary step towards a full-fledged early-warning system for the unusual volatile market and liquidity fluctuation conditions. However, empirical analysis on testing the relationship between high-frequency informed trading and market liquidity has not yet been formally conducted in previous market microstructure literature. On the basis of intraday high-frequency tick transaction data of Chinese Stock Index Futures, we use VPIN as a proxy of high-frequency market toxicity induced by informed trading, aiming to test on the feedback effect on VPIN metric and liquidity for literature contribution, as well as to evaluate a market toxicity proxy for both regulators and investors of financial markets. According to two high-volatile events -- the Fat Finger Event and the Money Shortage Event, we assess the predictive ability of the three VPIN metrics according to three different trading classification algorithms -- Lee-Ready Classification (LR), Tick Rule Classification (TR), and Bulk Volume Classification (BV). Taking the method of conditional probability analysis and multiple regression, we examine the association between VPIN and toxic-induced market volatility. On the basis of Vector Auto-Regression (VAR) models, we adopt Granger causality test and impulse-response analysis, further testing the hypothesis on the feedback effect of VPIN and high-frequency liquidity.

Our results show that the VPIN metric can be adapted in the Chinese market, as the corresponding CDF of VPIN indicating the high toxicity of stock market reaches an extreme level before high fluctuations in both the intraday analysis of the

Fat Finger Event and the period analysis of the Money Shortage Event. We present that BV-VPIN has the best effect on the validity of VPIN metrics among the three algorithms. We find a positive association between VPIN and toxic-induced volatility, which supports the viewpoints of Easley et al. (2012a) in the dispute from an out-of-sample market. Most importantly, we document a downward spiral or positive feedback effect, demonstrating a vicious circle between VPIN and high-frequency liquidity. VPIN is boosted up by the shock of negative liquidity, while it in turn leads to a deeper drain of liquidity.

Summarizing from our empirical research, we conclude that VPIN can be employed as an effective risk management tool and can be put in practice under the prevalent high-frequency trading mechanism of the current financial world. More importantly, through our empirical study, we offer an economic interpretation of the empirically identified relationship between VPIN and market liquidity, as well as providing empirical evidence reflecting an intrinsic game between informed traders and market makers when facing toxic information in the high-frequency trading market.

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Appendix A -- PIN Estimation Model (1996)

Appendix A presents the algorithm of PIN estimation model. As an information-based market microstructure model, PIN represents the probability of information-based trading. It is a measure of information asymmetry based on theoretical framework of Easley and O'Hara (1987, 1992). The original PIN model is proposed by Easley et al. (1996), known as EKOP model as well. PIN model is the basis of the high frequency VPIN model. The proposition of PIN model is the first innovation that leads us the exploration of direct measurement of informed trading. PIN is measured by a microstructure model, which has a key procedure of maximized likelihood estimation.

Liquidity providers and traders constitute two parts of the whole trading process. We know that traders can be divided into informed traders and uninformed traders (Copeland & Galai, 1983). For the traders who are not informed with new information, the buy and sell orders are modeled as two Poisson processes, with the buy arrival rate ε_b and the sell arrival rate ε_s . These two arrival rates are the uninformed rates. For the traders who are informed with new information, the buy and sell orders are modeled as two Poisson processes as well, with the difference of adding a daily arrival rate μ. This arrival rate is the informed rate.

Informed traders only perform trading process with the days that information events occur. The model set the probability of information-based event happening as α, so the probability that the information-based event does not occur is $1-\alpha$. Hence, if there is good news happening between trading days, informed traders will buy with the probability of $1-\delta$; if there is bad news happening, they will sell with the probability of δ.

Bid-Ask spread measures the liquidity, it explains the range at which market makers are willing to provide liquidity. The calculation of PIN takes this point as a focus to develop the following calculation steps. From the model demonstrated from Fig.2, the occurring probability of three situations according to good news, bad news and no news can be explained by:

$$P(t) = (P_n(t), P_b(t), P_g(t)) \Rightarrow P(0) = (1-\alpha, \alpha\delta, \alpha(1-\delta))$$

Then according to the probability above, we can get the expected value of the security's price:

$$E[S_t] = (1-\alpha_t)S_0 + \alpha_t[\delta_t S_B + (1-\delta_t)S_G]$$

In order to avoid losses from informed traders, market makers reach breakeven at a bid level:

$$E[B_t] = E[S_t] - \frac{\mu\alpha_t\delta_t}{\epsilon + \mu\alpha_t\delta_t}(E[S_t] - S_B)$$

And at an ask level:

$$E[A_t] = E[S_t] + \frac{\mu\alpha_t(1-\delta_t)}{\epsilon + \mu\alpha_t(1-\delta_t)}(S_G - E[S_t])$$

Hence, the breakeven at bid-ask spread is the difference between the breakeven between the bid level and the ask level:

$$\Sigma\,(t) = E[A_t - B_t] = \frac{\mu\alpha_t(1-\delta_t)}{\epsilon + \mu\alpha_t(1-\delta_t)}(S_G - E[S_t]) + \frac{\mu\alpha_t\delta_t}{\epsilon + \mu\alpha_t\delta_t}(E[S_t] - S_B)$$

EKOP (1996) consider the standard case. At the first stage, when the probability of good news happening equals to the probability of bad news happening, $1-\delta=\delta, \delta=0.5$. Then, we can substitute this result to the expected breakeven at bid-ask spread:

$$\delta_t = \frac{1}{2} \Rightarrow E[A_t - B_t] = \frac{\alpha_t \mu}{\alpha_t \mu + 2\epsilon}(S_G - S_B)$$

PIN factor determines the range at which market makers provide liquidity. So from the latest formula of the breakeven at bid-ask spread:

$$PIN_t = \frac{\alpha_t \mu}{\alpha_t \mu + 2\epsilon}$$

This is the main calculated formula of PIN. The numerator is the arrival rate of all informed orders, in other words, it is the probability based on informed orders. The denominator $\alpha_t \mu + 2\epsilon$ is actually $\alpha_t \mu + \epsilon_b + \epsilon_s$, namely the arrival rate of all trading orders. We can get the practical meaning from the extreme values of PIN. If PIN equals to 0, there is no adverse selection risk, and if PIN equals to 1 means that all trades are made by informed traders. Further, if PIN changes unexpectedly, there will be loss of liquidity providers. Hence, the liquidity providers should accurately estimate their PIN to ensure the optimized quotation of entering the market.

There is no direct value of the parameters from the PIN calculation equation, so the calculation of PIN uses maximized likelihood estimation method to estimate the 5 non-observable parameters, and PIN is deducted according to these estimations.

The likelihood function of B buy trades and S sell trades on a single transaction day is:

$$L\big((B,S)\big|\theta\big) = (1-\alpha)e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!}$$

$$+\alpha\delta e^{-\varepsilon_b}\frac{(\varepsilon_b)^B}{B!}e^{-(\varepsilon_s+\mu)}\frac{(\varepsilon_s+\mu)^S}{S!}$$

$$+\alpha(1-\delta)e^{-(\varepsilon_b+\mu)}\frac{(\varepsilon_b+\mu)^B}{B!}e^{-\varepsilon_s}\frac{(\varepsilon_s)^S}{S!}$$

The likelihood function is a mixture of 3 Poisson probabilities, weighted by the probability $\alpha(1-\delta)$ for having a day of good news, $\alpha\delta$ for bad news, and $(1-\alpha)$ for no news. In a single transaction day, B means the total buy trades, S means the total sell trades, and $\theta = (\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s)$ acts as the parameter vector including 5 parameters needed for the calculation of PIN. Considering the characteristics of independence between days, we can use the product of the likelihood function on a daily basis to represent the likelihood function across J days:

$$L(M|\theta) = \prod_{j=1}^{J} L(\theta|B_j, S_j)$$

Comparatively from the single day basis, B_j means the total buy trades and S_j means the total sell trades from the 1st day to the Jth day. M = [(B_1, S_1),…, (B_j, S_j)] represents the data set. Hence, given the dataset M, we maximize the likelihood function of the mixture of 3 Poisson probabilities, and get the estimates for the 5 parameters $(\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s)$ of the PIN model. After the estimation of the 5 parameters, we get PIN values from the PIN calculation formula.

Appendix B -- High Frequency Liquidity Benchmarks

Appendix B introduces four high-frequency liquidity benchmarks used in our high frequency liquidity research, namely Effective Spread, Realized Spread, Quoted Spread, and Permanent Price Impact.

Benchmark 1: Effective Spread

$$Effective\ Spread = 2 \cdot |\ln(P_k) - \ln(M_k)|$$

Our first high-frequency liquidity benchmark is the Effective Spread. It is an estimate of the cost of trading for a hypothetical transaction of the average trade size used to calculate it. P_k is the price of the k^{th} trade and M_k is the midpoint price of the consolidated BBO (Best-Bid-Offer) prevailing at the time of the k^{th} trade.

Benchmark 2: Realized Spread

$$Realized\ Spread = 2 \cdot |\ln(P_k) - \ln(M_{k+5})|$$

Our second high-frequency liquidity benchmark is the Realized Spread, proposed by Huang and Stoll (1996). This liquidity measure is designed to capture only the temporary component of the effective spread. M_{k+5} is the midpoint price of the consolidated BBO (Best-Bid-Offer) prevailing 5-min after the k^{th} transaction.

Benchmark 3: Quoted Spread

$$Quoted\ Spread = (Ask - Bid)/((Ask + Bid)/2)$$

Our third high-frequency liquidity benchmark is the Quoted Spread. This measure is the calculation using best ask and the best quote in a specific time interval, using only the level-2 transaction data.

Benchmark 4: Permanent Price Impact

$$Permanent\ Price\ Impact = Effective\ Spread - Realized\ Spread$$
$$= 2 \cdot |\ln(M_{k+5}) - \ln(M_k)|$$

Our fourth high-frequency liquidity benchmark is the Permanent Price Impact by Huang and Stoll (1996). This price impact method takes an eye on the change of prices and quotes after a signed trade. The permanent price impact of a given trade is just the increase or decrease in the midpoint price over a 5-min interval beginning at the time of the buyer or seller initiated transaction. It is mathematically equal to the effective spread minus the realized spread. M_{k+5} is the midpoint price of the consolidated BBO (Best-Bid-Offer) prevailing 5-min after the k^{th} transaction.

Appendix C -- Tables

Table 1: Summary of Liquidity Benchmarks and Proxies.

Liquidity Proxies in Previous Literature	
Proxy	**Description**
Effective Spread	$Effective\ Spread = 2 \cdot \lvert \ln(P_k) - \ln(M_k) \rvert$
Aggregated Effective Spread	$Aggregated\ Effective\ Spread = \begin{cases} 2 \cdot (P_k - m_k) & for\ buys \\ 2 \cdot (m_k - P_k) & for\ sells \end{cases}$
Quoted Spread	$Quoted\ Spread = (Ask - Bid)/((Ask + Bid)/2)$
Static Price Impact	$Static\ Price\ Impact = \frac{[(\$Effective\ Spread_{Big\ Orders}/\bar{P}) - \$Effective\ Spread_{Small\ Orders}/\bar{P})]}{[Ave\ Trade\ Size_{Big\ Orders} - Ave\ Trade\ Size_{Small\ Orders}]}$
Roll Roll (1984)	$Roll = \begin{cases} \frac{2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}}{\bar{P}} & when\ Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & when\ Cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases}$
Amivest Cooper, Groth, and Avera (1985)	$Amivest = Average(\frac{Volume_t}{\lvert r_t \rvert})$
Realized Spread Huang and Stoll (1996)	$Realized\ Spread = 2 \cdot \lvert \ln(P_k) - \ln(M_{k+5}) \rvert$
Permanent Price Impact Huang and Stoll (1996)	$Permanent\ Price\ Impact = Effective\ Spread - Realized\ Spread$ $= 2 \cdot \lvert \ln(M_{k+5}) - \ln(M_k) \rvert$
LOT Mixed Lesmond, Ogden, and Trzeinka (1999)	$LOT\ Mixed = \alpha_2 - \alpha_1$ (transaction cost to buy − transaction cost to sell)
Zeros Lesmond, Ogden, and Trzeinka (1999)	$Zeros = \frac{\#\ of\ zero\ return\ days}{\#\ of\ trading\ days + \#\ of\ nontrade\ days\ in\ a\ given\ stock\ month}$
Amihud Amihud (2002)	$Amihud = Average(\frac{\lvert r_t \rvert}{Volume_t})$
Pastor and Stambaugh Gamma Pastor and Stambaugh (2002)	$r^e_{t+1} = \theta + \phi r_t + \Gamma sign(r^e_t)(Volume_t) + \varepsilon_t$
Gibbs Hasbrouck (2004)	*Bayesian Estimation of Roll Model*
Lambda Hasbrouck (2006)	$r_n = (\text{Five Minutes Price Impact}) \cdot S_n + u_n$
Extended Roll Holden (2009)	$Extended\ Roll = \begin{cases} \frac{2\sqrt{-Cov(\Delta P^*_t, \Delta P^*_{t+1})}}{\bar{P}} & when\ Cov(\Delta P^*_t, \Delta P^*_{t+1}) < 0 \\ 0 & when\ Cov(\Delta P^*_t, \Delta P^*_{t+1}) \geq 0 \end{cases}$
Effective Tick Goyenko, Holden, and Trzeinka (2009) & Holden (2009)	$Effective\ Tick = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\bar{P}_i}$
LOT Y-split Goyenko, Holden, and Trzeinka (2009)	$LOT\ Mixed = \alpha_2 - \alpha_1$ (Compare to LOT Mixed: different region classification based on the market return; no upper bond cap)
Zeros2 Goyenko, Holden, and Trzeinka (2009)	$Zeros2 = \frac{\#\ of\ positive\ volume\ days\ with\ zero\ return}{\#\ of\ trading\ days + \#\ of\ nontrade\ days\ in\ a\ given\ stock\ month}$
Extended Amihud Goyenko, Holden, and Trzeinka (2009)	$Extended\ Amihud = \frac{Percent\ Cost\ Proxy}{Average\ Daily\ Currency\ Volume}$

Table 1 summarizes the liquidity proxies proposed in previous literature. High-frequency benchmarks are listed such as Effective Spread, Realized Spread, Quoted Spread, Static Price Impact, Permanent Price Impact, and Lambda. Developments of low-frequency liquidity proxies are listed on the basis of time line: Roll Method (1984), Amivest (1985), Permanent Price Impact (1996), LOT Mixed (1999), Zeros (1999), Amihud (2002), Pastor and Stambaugh Gamma (2002), Gibbs (2004), Extended Roll (2009), Effective Tick (2009), LOT Y-Split (2009), Extended Zeros (2009), and Extended Amihud (2009).

Table 2: Best Emerging Markets Worldwide (2014).

Table 2 shows the worldwide best emerging market in 2014. It helps explain our institutional background of Chinese market. Source is from Bloomberg Visual Data.

Rank (By Avg. GDP Growth 2014 - 2015)	Country	Avg. GDP Growth 2014 - 2015	Avg. Inflation Rate 2014 - 2015	Avg. Total Investment as % of GDP 2014 - 2015
1	China	7.35%	3.15%	48.54%
2	Panama	6.70%	4.15%	27.04%
3	Philippines	6.13%	3.90%	19.17%
4	Indonesia	5.72%	5.93%	33.82%
5	Peru	5.53%	2.60%	28.50%
6	India	5.15%	8.58%	35.15%
7	Malaysia	5.00%	3.10%	27.66%
8	Colombia	4.58%	2.95%	23.39%
9	Thailand	4.50%	2.65%	31.48%
10	Morocco	4.37%	2.50%	35.21%

Table 3: VPIN Metric Procedure -- Sample from Aug 16, 2013.

Table 3 shows a small sample from our data. This part of transaction data corresponds to the first several seconds from 9:30:00 to 9:30:18 on Aug 16, 2013 of Chinese Stock Index Market. Basic components for VPIN calculation are shown -- time, price and volume.

Time	Price	Volume	Time	Price	Volume	Time	Price	Volume
-	-	-	09:30:06	2328.4	16	09:30:13	2327.2	14
-	-	-	09:30:06	2328.2	44	09:30:13	2327.2	28
09:30:00	2327.4	14	09:30:07	2328.2	62	09:30:14	2327.2	18
09:30:00	2328	143	09:30:07	2328	8	09:30:14	2327.4	21
09:30:01	2328.4	130	09:30:08	2328	33	09:30:15	2327.6	9
09:30:01	2328.2	154	09:30:08	2327.6	23	09:30:15	2327.2	30
09:30:02	2327.8	82	09:30:09	2327.6	18	09:30:16	2327.8	16
09:30:02	2328	69	09:30:09	2327	105	09:30:16	2327.6	18
09:30:03	2327.6	47	09:30:10	2327	17	09:30:17	2327.8	48
09:30:03	2327.6	124	09:30:10	2327.2	25	09:30:17	2327.4	55
09:30:04	2327.4	75	09:30:11	2327.4	25	09:30:18	2327.6	9
09:30:04	2327.4	17	09:30:11	2327	13	09:30:18	2327.4	16
09:30:05	2327.8	21	09:30:12	2327.2	52	-	-	-
09:30:05	2328	33	09:30:12	2327	18	-	-	-

Table 4: VPIN Metric Procedure - Time Bars.

Table 4 explains the constitution of time bars from our small sample. Each time bar contains the period of 1 minute. TB price change shows the change of the price in each bar. TB volume reflects the aggregated volume from all the trades in the corresponding minute.

Time bar (TB)	TB price change (ΔP)	TB volume
-	-	-
9:30:01 - 9:31:00	-	-
9:31:01 - 9:32:00	-1.6	2002
9:32:01 - 9:33:00	4.6	4561
9:33:01 - 9:34:00	-2	2350
9:34:01 - 9:35:00	-2	3031
9:35:01 - 9:36:00	0.4	3096
9:36:01 - 9:37:00	-	-

Table 5: VPIN Metric Procedure - Volume Bucketing and Bulk Classification.

Table 5 interprets the process of volume buckets constitution and the classification of buys and sells using the bulk volume classification method. Components for computing the volume buckets are listed: time bar, price change in time bar, volume in time bar, accumulated volume bucket, number of bucket, the standardized normal distribution, the complementary part of the standardized normal distribution, buy volume in time bar, and sell volume in time bar. Columns 1 – 5 show that when buckets are filled with the volume of 9248 shares (VBS), the excess shares from the last time bar of a bucket are assigned to the next bucket. Columns 6 – 9 show bulk volume classification method. The main method is to calculate the standardized normal distribution of a price change, then to multiply the TB volume of Column 4 by the number of Column 6 and Column 7 to get the buy volume and sell volume, respectively.

Time Bar (TB)	TB price change	TB volume	Accumulated volume	#Bucket	$Z(\Delta P/\sigma_{\Delta P})$	$1 - Z(\Delta P/\sigma_{\Delta P})$	Buy volume	Sell volume
-	-	-	-	#18167	-	-	-	-
9:30	-	-		#18167	-	-	-	-
9:31	**-1**	**277**	**9248**	**#18167**	**0.3052**	**0.6948**	**84.5**	**192.5**
9:31	-1	1756	1756	#18168	0.3052	0.6948	535.9	1220.1
9:32	3.6	4515	6271	#18168	0.9667	0.0333	4364.7	150.3
9:33	-1	2465	8736	#18168	0.3052	0.6948	752.2	1712.8
9:34	**-2.6**	**512**	**9248**	**#18168**	**0.0926**	**0.9074**	**47.4**	**464.6**
9:34	-2.6	2545	2545	#18169	0.0926	0.9074	235.6	2309.4
9:35	-0.2	3126	5671	#18169	0.4594	0.5406	1436.1	1689.9
9:36	-	-	-	#18169	-	-	-	-

Table 6: VPIN Metric Procedure - Order Imbalance.

Table 6 shows order imbalance for the first six buckets of Aug 16, 2013. Columns 2 and 3 are the sum of all buy-initiated (sell-initiated) volume for the corresponding time bars of each bucket, and the sum of these two columns in each bucket equals to the number of VBS. Order imbalance is just the absolute difference between the two columns, shown in Column 4. Column 5 and 6 indicates the initial and final time bar for each assigned bucket.

#Bucket	Aggregated buy volume	Aggregated sell volume	Order imbalance	Initial time bar	Final time bar
#18168	5700.2	3547.8	2152.6	09:31:00	09:34:00
#18169	3267.9	5980.1	2712.2	09:34:00	09:37:00
#18170	6820.5	2427.4	4393.1	09:37:00	09:41:00
#18171	4622.9	4625.1	2.2	09:41:00	09:44:00
#18172	4653.5	4594.4	59.1	09:44:00	09:49:00
#18173	1509.6	7738.4	6228.8	09:49:00	09:52:00

Table 7: VPIN Metric Procedure - VPIN and Sample Length.

Table 7 presents the first ten result of VPIN calculation for Aug 16, 2013, with 1-min time bars, 50 volume buckets and a sample length of 50 buckets. VPIN calculation is the ratio of the sum of the bucket order imbalances in a sample length and the total number of trades. The VPIN is updated after the completion of each bucket in a rolling-window process. With respect to the final bucket, when bucket #50 is filled, the first VPIN is calculated, and the second VPIN has the buckets from #2 to #51.

Obs	VPIN	Initial #Bucket	Final #Bucket
1	0.248515519	#1	#50
2	0.245059885	#2	#51
3	0.250523585	#3	#52
4	0.255606093	#4	#53
5	0.24788895	#5	#54
6	0.23739808	#6	#55
7	0.249343998	#7	#56
8	0.252235466	#8	#57
9	0.261112958	#9	#58
10	0.274875275	#10	#59
-	-	-	-

Table 8: BV-VPIN Statistics of 2012 to 2013.

Table 8 presents the basic statistics for the BV-VPIN series calculated by different buy-sell classification algorithms. This is the statistics for the whole 2-year sample from 2012 to 2013 in Chinese Stock Index Futures market. Here we use 1-min time bars, 50 volume buckets and a sample length of 50 buckets.

Statistics	VPIN 1-50-50
Mean	0.2961
Median	0.2859
Std.deviation	0.0861
Max	0.6914
Min	0.0951
# Obs.	23951

Table 9: Descriptive Statistics of Volatility Proxies.

Table 9 shows the descriptive statistics of two different proxies of market volatility, the absolute return and the market risk, respectively. The absolute return is the absolute value of returns in each volume bucket, and the market risk is calculated after dividing each volume bucket into ten sub volume buckets, getting the standard deviation of returns in each volume bucket. Descriptive statistics include the mean, median, maximum, minimum, standard deviation, skewness, kurtosis, Q3 value (75%), and Q1 value (25%).

Proxies	Abs. Return	Market Risk
Mean	0.00119	0.00091
Median	0.00119	0.00091
Maximum	0.02093	0.00592
Minimum	0.00000	0.00012
Std. Deviation	0.00113	0.00061
Skewness	4.07902	3.39559
Kurtosis	37.9112	16.9304
Q3	0.00159	0.00103
Q1	0.00045	0.00056

Table 10: Descriptive Statistics of High-Frequency Liquidity Benchmarks.

Table 10 shows the descriptive statistics of four high-frequency liquidity benchmarks. These benchmarks are the Effective Spread, the Realized Spread, the Quoted Spread, and the Price Impact. Descriptive statistics include the mean, median, maximum, minimum, standard deviation, skewness, and kurtosis.

Benchmarks	Effective Spread	Realized Spread	Quoted Spread	Price Impact
Mean	0.00011	0.00602	0.00011	0.00602
Median	0.00009	0.00456	0.00009	0.00457
Maximum	0.00065	0.08841	0.00057	0.08822
Minimum	0.00000	0.00000	0.00007	0.00000
Std. Deviation	0.00006	0.00589	0.00005	0.00588
Skewness	1.61972	3.01861	2.19262	3.01796
Kurtosis	3.89014	18.2682	5.81507	18.2643

Table 11: Robustness Check of BV-VPIN Metric.

Table 11 expresses the statistics of our robustness check procedure. This table contains eight combinations of the three key VPIN calculation variables -- time bar, VBS, and sample length.

Combination	Mean	Median	Std. Deviation	Max	Min	Range
1-1-5	0.0617	0.0609	0.0233	0.1562	0.0171	0.1391
1-1-20	0.0543	0.0537	0.0132	0.0843	0.0271	0.0573
1-50-50	0.2961	0.2859	0.0861	0.6914	0.0951	0.5963
1-50-250	0.2916	0.2814	0.0669	0.5081	0.1577	0.3504
5-1-5	0.1071	0.1064	0.0403	0.2785	0.0239	0.2545
5-1-20	0.0943	0.0933	0.0231	0.1543	0.0416	0.1127
5-50-50	0.3942	0.3807	0.1126	0.8652	0.1271	0.7382
5-50-250	0.3879	0.3769	0.0876	0.6623	0.1989	0.4634

Table 12: Pearson Correlation Coefficients.

Table 12 presents descriptive statistics of VPIN and market volatility proxies. Two proxies of market volatility are the market risk and the absolute return. The proxy of the trade intensity is the trade size. VPIN and trade intensity are at prior level. *** denotes a significance level of 1%. Coefficients and p-value are shown in the table.

Pearson Correlation Coefficients			
	Market Risk (t)	Abs. Return (t)	VPIN (t-1)
Market Risk (t)	1.0000		
Abs. Return (t)	0.3498 (0.000)	1.0000	
VPIN (t-1)	0.1174*** (0.000)	0.0872*** (0.000)	1.0000

Table 13 (a): Conditional Probabilities - Absolute Return Conditioning on VPIN.

Table 13 (a) presents the conditional probability tendency analysis on the distribution of VPIN and market volatility. The VPIN metric is BV-VPIN. The market volatility proxy here is the market risk. We examine the distribution of absolute returns over the subsequent volume bucket conditional on VPIN in each of the twenty 5-percentile bins. Twenty conditional distributions are set up, representing a distribution of the absolute returns conditioned on the prior level of VPIN.

		Absolute Return Between Two Consecutive Buckets								
		0.25%	**0.50%**	**0.75%**	**1.00%**	**1.25%**	**1.50%**	**1.75%**	**2%**	**>2.00%**
VPIN Percentiles	**0.05**	75.58%	13.07%	3.40%	2.28%	2.27%	0.57%	0.57%	0.56%	1.70%
	0.10	73.86%	15.34%	4.55%	2.27%	2.28%	0.57%	0.57%	0.00%	0.56%
	0.15	74.01%	14.12%	7.35%	2.26%	0.56%	1.13%	0.57%	0.00%	0.00%
	0.20	73.29%	14.77%	5.69%	3.41%	2.27%	0.00%	0.00%	0.00%	0.57%
	0.25	73.99%	13.00%	7.35%	3.95%	0.57%	0.00%	0.00%	0.57%	0.57%
	0.30	72.71%	10.80%	7.95%	3.41%	1.71%	0.57%	1.14%	0.00%	1.71%
	0.35	72.29%	14.69%	3.39%	3.96%	1.13%	1.13%	0.57%	1.14%	1.70%
	0.40	76.70%	10.80%	3.97%	4.55%	2.27%	0.00%	0.00%	0.57%	1.14%
	0.45	77.39%	11.30%	5.08%	1.70%	1.12%	1.13%	0.57%	0.57%	1.14%
	0.50	75.57%	13.06%	5.12%	3.97%	1.14%	0.00%	0.00%	0.00%	1.14%
	0.55	71.59%	15.34%	5.11%	3.41%	1.70%	0.57%	1.14%	0.00%	1.14%
	0.60	71.18%	13.00%	8.47%	3.39%	1.70%	1.14%	1.14%	0.00%	0.00%
	0.65	69.88%	15.91%	7.96%	2.27%	1.70%	1.14%	0.57%	0.00%	0.57%
	0.70	68.92%	13.56%	7.91%	4.52%	1.13%	1.70%	1.69%	0.00%	0.57%
	0.75	71.63%	14.77%	6.25%	3.41%	0.57%	1.13%	0.00%	0.00%	2.24%
	0.80	75.70%	11.30%	4.52%	4.52%	0.66%	1.03%	0.56%	0.57%	1.14%
	0.85	69.32%	13.06%	6.82%	3.41%	3.41%	1.14%	0.56%	1.14%	1.14%
	0.90	70.62%	7.35%	8.46%	3.96%	2.83%	1.69%	1.70%	2.26%	1.13%
	0.95	69.88%	13.07%	6.25%	4.54%	2.28%	2.27%	0.57%	0.00%	1.14%
	1.00	59.88%	11.30%	12.43%	4.52%	3.96%	2.82%	1.70%	1.15%	2.24%

$$Prob\left(\left|\frac{P_\tau}{P_{\tau-1}} - 1\right| \middle| VPIN_{\tau-1}\right)$$

Table 13 (b): Conditional Probabilities - VPIN Conditioning on Absolute Return.

Table 13 (b) demonstrates the conditional probabilities, in the content of the VPIN conditioning on the absolute return. We examine the distribution of VPIN in the prior bucket conditioning on the absolute returns between the prior and current bucket. Each column provides the distribution of prior VPINs conditional on the bin of size on the absolute returns at an interval of 0.25%.

	Absolute Return Between Two Consecutive Buckets									
VPIN Percentiles		0.25%	0.50%	0.75%	1.00%	1.25%	1.50%	1.75%	2.00%	>2.00%
	0.05	5.11%	5.18%	2.67%	2.58%	0.00%	0.00%	0.00%	0.00%	0.00%
	0.10	5.15%	5.63%	4.00%	2.58%	1.49%	3.23%	0.00%	0.00%	0.00%
	0.15	5.11%	5.63%	5.77%	3.45%	1.49%	0.00%	4.34%	0.00%	0.00%
	0.20	5.04%	5.86%	4.45%	5.18%	4.48%	0.00%	0.00%	0.00%	0.00%
	0.25	5.11%	5.18%	5.78%	5.18%	1.49%	0.00%	0.00%	6.25%	0.00%
	0.30	5.07%	3.60%	6.22%	5.17%	5.97%	3.22%	4.34%	0.00%	0.00%
	0.35	4.95%	6.08%	2.67%	6.04%	4.48%	3.23%	0.00%	6.25%	0.00%
	0.40	5.27%	4.06%	3.55%	6.03%	5.97%	0.00%	0.00%	6.25%	2.27%
	0.45	5.46%	4.50%	4.00%	2.59%	2.95%	0.00%	8.70%	0.00%	2.27%
	0.50	5.27%	4.73%	3.56%	6.06%	1.50%	0.00%	0.00%	0.00%	0.00%
	0.55	5.00%	5.63%	3.55%	5.18%	5.97%	0.00%	4.35%	6.25%	2.27%
	0.60	4.95%	4.96%	6.22%	5.99%	4.50%	3.23%	4.35%	0.00%	0.00%
	0.65	4.84%	6.08%	6.67%	2.59%	2.99%	6.45%	4.35%	0.00%	2.27%
	0.70	4.76%	5.40%	5.78%	5.18%	2.98%	9.68%	4.35%	6.25%	2.27%
	0.75	4.95%	5.86%	4.44%	5.17%	2.99%	3.23%	0.00%	0.00%	4.54%
	0.80	5.31%	3.83%	3.56%	6.03%	5.97%	6.45%	0.00%	6.25%	4.54%
	0.85	4.72%	5.18%	5.78%	4.31%	8.95%	6.45%	8.70%	6.25%	6.82%
	0.90	4.88%	2.93%	7.55%	3.45%	8.95%	9.95%	13.05%	12.50%	13.63%
	0.95	4.91%	4.73%	5.34%	8.62%	13.44%	19.36%	17.39%	18.75%	18.18%
	1.00	4.14%	4.95%	8.44%	8.62%	13.44%	25.52%	26.08%	25.00%	40.94%

$$Prob\left(VPIN_{\tau-1} \mid \left|\frac{P_\tau}{P_{\tau-1}} - 1\right|\right)$$

Table 14 (a): Pearson Correlation for the Analysis of Market Risk and VPIN.

Table 14 (a) demonstrates correlation coefficients of multiple regression models of market risk and VPIN. Coefficient and p-value are shown in the table. Two control variables are the lag of market risk and the lag of trade intensity. *** indicates that the result is significant at 1%-level.

Pearson Correlation Coefficients (Market Risk)				
	Market Risk (t)	VPIN (t-1)	Market Risk (t-1)	Trade Intensity (t-1)
Market Risk (t)	1.0000			
VPIN (t-1)	0.1174*** (0.000)	1.0000		
Market Risk (t-1)	0.5669*** (0.000)	-0.001 (0.9735)	1.0000	
Trade Intensity (t-1)	0.0374*** (0.000)	0.1677 (0.000)	-0.023 (0.001)	1.0000

Table 14 (b): Pearson Correlation for the Analysis of Absolute Return and VPIN.

Table 14 (b) demonstrates correlation coefficients of multiple regression models of absolute return and VPIN. Coefficient and p-value are shown in the table. Two control variables are the lag of absolute return and the lag of trade intensity. *** indicates that the result is significant at 1%-level.

Pearson Correlation Coefficients (Abs. Return)				
	Abs. Return (t)	VPIN (t-1)	Abs. Return (t-1)	Trade Intensity (t-1)
Abs. Return (t)	1.0000			
VPIN (t-1)	0.0861*** (0.000)	1.0000		
Abs. Return (t-1)	0.1104*** (0.000)	0.1137 (0.000)	1.0000	
Trade Intensity (t-1)	-0.0297*** (0.000)	0.2703 (0.000)	0.2127 (0.000)	1.0000

Table 14 (c): Multiple Regression Analysis of VPIN and Market Volatility.

Table 14 demonstrates multiple regression models of VPIN and market volatility. All the variables are taking natural logarithm following the thought of Easley et al. (2008). Panel A presents four models using the market risk as the proxy of market volatility. Panel B presents four models using the absolute return as the proxy of market volatility. Four models are demonstrated for testing the predictive power of VPIN to market volatility. Model 1 considers the individual predictability between the prior level of VPIN and the current level of absolute return. Model 2 takes the lag of volatility into evaluation while Model 3 controls for lagged trade intensity. Model 4 takes both for both two control variables into evaluation. Coefficient, p-value and t-statistics are shown in the table.

Multiple Regression Analysis of VPIN and Market Volatility				
Panel A: Market Risk (t)				
	Model 1	**Model 2**	**Model 3**	**Model 4**
VPIN (t-1)	0.0831*** (0.000) [17.35]	0.0832*** (0.000) [21.15]	0.0809*** (0.000) [16.66]	0.0794*** (0.000) [19.93]
Market Risk (t-1)		0.1282*** (0.000) [102.03]		0.1284*** (0.000) [102.20]
Trade Intensity (t-1)			0.002*** (0.008) [2.66]	0.004*** (0.000) [5.59]
Const.	0.066 (0.000) [44.78]	0.0406 (0.000) [32.83]	0.066 (0.000) [44.73]	0.0405 (0.000) [32.72]
R-square	0.0138	0.3352	0.0141	0.3361
Panel B: Abs. Return (t)				
	Model 1	**Model 2**	**Model 3**	**Model 4**
VPIN (t-1)	0.1157*** (0.000) [12.96]	0.1001*** (0.000) [11.20]	0.1365*** (0.000) [14.74]	0.1270*** (0.000) [13.78]
Abs. Return (t-1)		0.1011*** (0.000) [15.33]		0.1157*** (0.000) [17.28]
Trade Intensity (t-1)			-0.054*** (0.000) [-8.29]	-0.076*** (0.000) [-11.48]
Const.	0.8823 (0.000) [32.09]	0.8040 (0.000) [28.89]	0.9689 (0.000) [32.98]	0.9140 (0.000) [31.13]
R-square	0.0074	0.0177	0.0104	0.0234

Note: *** indicates that the result is significant at 1%-level, ** indicates that the result is significant at 5%-level, and * indicates the result is significant at 10%-level. The significance is reported based on two-tailed tests.

Table 15: Coefficients of Vector Auto-Regression (VAR) Model Constituted by High-Frequency Liquidity Benchmarks and VPIN.

Table 15 displays the coefficients of Vector Auto-Regression (VAR) Model, which is constituted by high-frequency liquidity benchmarks and VPIN.

$$\begin{pmatrix} \Delta Liquidity_t \\ \Delta VPIN_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{pmatrix} \phi_{11,1} & \phi_{12,1} \\ \phi_{21,1} & \phi_{22,1} \end{pmatrix} \begin{pmatrix} \Delta Liquidity_{t-1} \\ \Delta VPIN_{t-1} \end{pmatrix} + \begin{pmatrix} \phi_{11,2} & \phi_{12,2} \\ \phi_{21,2} & \phi_{22,2} \end{pmatrix} \begin{pmatrix} \Delta Liquidity_{t-2} \\ \Delta VPIN_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix}$$

Four high-frequency liquidity benchmarks are displayed in the table, with Panel A of the effective spread, Panel B of the realized spread, Panel C of the quoted spread, and Panel D of the price impact. 8 coefficients are showed in the table. $\phi_{11,1}$ stands for the coefficient of $\Delta Liquidity_{t-1}$ to $\Delta Liquidity_t$; $\phi_{11,2}$ stands for the coefficient of $\Delta Liquidity_{t-2}$ to $\Delta Liquidity_t$; $\phi_{12,1}$ stands for the coefficient of $\Delta VPIN_{t-1}$ to $\Delta Liquidity_t$ $\phi_{12,2}$ stands for the coefficient of $\Delta VPIN_{t-2}$ to $\Delta Liquidity_t$; $\phi_{21,1}$ stands for the coefficient of $\Delta Liquidity_{t-1}$ to $\Delta VPIN_t$; $\phi_{21,2}$ stands for the coefficient of $\Delta Liquidity_{t-2}$ to $\Delta VPIN_t$; $\phi_{22,1}$ stands for the coefficient of $\Delta VPIN_{t-1}$ to $\Delta VPIN_t$; $\phi_{22,2}$ stands for the coefficient of $\Delta VPIN_{t-2}$ to $\Delta VPIN_t$. The variables are formalized to meet the scale of VPIN. Coefficients, standard error, and t-statistics are shown in the table. t-statistics > 1.65 means p-value < 10%; t-statistics > 1.96 means p-value < 5%; t-statistics > 2.58 means p-value < 1%.

Benchmarks	Coefficients							
	$\phi_{11,1}$	$\phi_{11,2}$	$\phi_{12,1}$	$\phi_{12,2}$	$\phi_{21,1}$	$\phi_{21,2}$	$\phi_{22,1}$	$\phi_{22,2}$
Panel A: Effective Spread								
Effective Spread	0.337	-0.087	0.044	0.026	0.011	0.009	0.114	0.058
	(0.007)	(0.007)	(0.009)	(0.009)	(0.005)	(0.005)	(0.007)	(0.007)
	[49.37]	[-12.72]	[4.763]	[2.774]	[2.104]	[1.837]	[16.68]	[8.481]
Adj. R-square	0.1055				0.0199			
Akaike Information Criterion	11.957							
Panel B: Realized Spread								
Realized Spread	0.124	0.140	0.025	0.009	0.036	0.048	0.112	0.056
	(0.007)	(0.007)	(0.005)	(0.005)	(0.009)	(0.009)	(0.007)	(0.007)
	[18.17]	[20.59]	[4.762]	[1.697]	[4.016]	[5.379]	[16.36]	[8.123]
Adj. R-square	0.0424				0.0208			
Akaike Information Criterion	10.798							
Panel C: Quoted Spread								
Quoted Spread	0.380	-0.096	0.043	0.027	0.006	0.019	0.114	0.058
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.006)	(0.007)	(0.007)
	[55.64]	[-14.08]	[5.083]	[3.123]	[1.104]	[3.618]	[16.71]	[8.427]
Adj. R-square	0.131				0.0193			
Akaike Information Criterion	11.788							
Panel D: Price Impact								
Price Impact	0.123	0.139	0.025	0.009	0.036	0.048	0.112	0.056
	(0.007)	(0.007)	(0.005)	(0.005)	(0.008)	(0.009)	(0.007)	(0.007)
	[18.14]	[20.47]	[4.805]	[1.722]	[4.031]	[5.298]	[16.36]	[8.126]
Adj. R-square	0.0421				0.0208			
Akaike Information Criterion	10.797							

Table 16: Granger Causality Test -- Liquidity and VPIN.

Table 16 presents the Eviews results from Granger Causality tests for four high-frequency liquidity benchmarks, testing whether there is Granger causality relationship between liquidity and VPIN. Chi-sq, degree of freedom, P-value, and rejection results are shown in the table. Test is based on Vector Auto-Regression model.

Panel A: Liq. does not Granger Cause VPIN (Null Hypothesis)				
Benchmarks	**Chi-sq**	**df**	**Prob.**	**Result**
Effective Spread	11.288	2	0.004***	**Reject**
Realized Spread	52.319	2	0.000***	**Reject**
Quoted Spread	19.422	2	0.000***	**Reject**
Price Impact	51.409	2	0.000***	**Reject**
Panel B: VPIN does not Granger Cause Liq. (Null Hypothesis)				
Benchmarks	**Chi-sq**	**df**	**Prob.**	**Result**
Effective Spread	34.053	2	0.000***	**Reject**
Realized Spread	27.816	2	0.000***	**Reject**
Quoted Spread	39.998	2	0.000***	**Reject**
Price Impact	28.395	2	0.000***	**Reject**

Note: *** indicates that the result is significant at 1%-level, ** indicates that the result is significant at 5%-level, and * indicates the result is significant at 10%-level. The significance is reported based on two-tailed tests.

Table 17: Coefficients of Vector Auto-Regression (VAR) Model Constituted by Market Volatility, High-Frequency Liquidity Benchmark, and VPIN.

$$\begin{pmatrix} \Delta Volatility_t \\ \Delta Liquidity_t \\ \Delta VPIN_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix} + \begin{pmatrix} \phi_{11,1} & \phi_{12,1} & \phi_{13,1} \\ \phi_{21,1} & \phi_{22,1} & \phi_{23,1} \\ \phi_{31,1} & \phi_{32,1} & \phi_{33,1} \end{pmatrix} \begin{pmatrix} \Delta Volatility_{t-1} \\ \Delta Liquidity_{t-1} \\ \Delta VPIN_{t-1} \end{pmatrix} + \begin{pmatrix} \phi_{11,2} & \phi_{12,2} & \phi_{13,2} \\ \phi_{21,2} & \phi_{22,2} & \phi_{23,2} \\ \phi_{31,2} & \phi_{32,2} & \phi_{33,2} \end{pmatrix} \begin{pmatrix} \Delta Volatility_{t-2} \\ \Delta Liquidity_{t-2} \\ \Delta VPIN_{t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix}$$

The proxy here for market volatility is the market risk; the benchmark of high-frequency liquidity is the realized spread. 18 coefficients are showed in the table. $\phi_{11,1}$ stands for the coefficient of $\Delta Volatility_{t-1}$ to $\Delta Volatility_t$; $\phi_{11,2}$ stands for the coefficient of $\Delta Volatility_{t-2}$ to $\Delta Volatility_t$; $\phi_{12,1}$ stands for the coefficient of $\Delta Liquidity_{t-1}$ to $\Delta Volatility_t$; $\phi_{12,2}$ stands for the coefficient of $\Delta Liquidity_{t-2}$ to $\Delta Volatility_t$; $\phi_{13,1}$ stands for the coefficient of $\Delta VPIN_{t-1}$ to $\Delta Volatility_t$; $\phi_{13,2}$ stands for the coefficient of $\Delta VPIN_{t-2}$ to $\Delta Volatility_t$; $\phi_{21,1}$ stands for the coefficient of $\Delta Volatility_{t-1}$ to $\Delta Liquidity_t$; $\phi_{21,2}$ stands for the coefficient of $\Delta Volatility_{t-2}$ to $\Delta Liquidity_t$; $\phi_{22,1}$ stands for the coefficient of $\Delta Liquidity_{t-1}$ to $\Delta Liquidity_t$; $\phi_{22,2}$ stands for the coefficient of $\Delta Liquidity_{t-2}$ to $\Delta Liquidity_t$; $\phi_{23,1}$ stands for the coefficient of $\Delta VPIN_{t-1}$ to $\Delta Liquidity_t$; $\phi_{23,2}$ stands for the coefficient of $\Delta VPIN_{t-2}$ to $\Delta Liquidity_t$; $\phi_{31,1}$ stands for the coefficient of $\Delta Volatility_{t-1}$ to $\Delta VPIN_t$; $\phi_{31,2}$ stands for the coefficient of $\Delta Volatility_{t-2}$ to $\Delta VPIN_t$; $\phi_{32,1}$ stands for the coefficient of $\Delta Liquidity_{t-1}$ to $\Delta VPIN_t$; $\phi_{32,2}$ stands for the coefficient of $\Delta Liquidity_{t-2}$ to $\Delta VPIN_t$; $\phi_{33,1}$ stands for the coefficient of $\Delta VPIN_{t-1}$ to $\Delta VPIN_t$; $\phi_{33,2}$ stands for the coefficient of $\Delta VPIN_{t-2}$ to $\Delta VPIN_t$. The variables are formalized to meet the scale of VPIN. Coefficients, standard error, and t-statistics are shown in the table. t-statistics > 1.65 means p-value < 10%; t-statistics > 1.96 means p-value < 5%; t-statistics > 2.58 means p-value < 1%.

	Realized Spread					
Coefficients	$\phi_{11,1}$	0.366 (0.007) [51.507]	$\phi_{21,1}$	-0.004 (0.022) [-0.167]	$\phi_{31,1}$	0.017 (0.029) [0.581]
	$\phi_{11,2}$	-0.082 (0.007) [-11.870]	$\phi_{21,2}$	0.119 (0.021) [5.653]	$\phi_{31,2}$	0.051 (0.028) [1.819]
	$\phi_{12,1}$	0.059 (0.002) [25.759]	$\phi_{22,1}$	0.122 (0.007) [17.256]	$\phi_{32,1}$	0.034 (0.009) [3.604]
	$\phi_{12,2}$	0.012 (0.002) [5.239]	$\phi_{22,2}$	0.128 (0.007) [17.798]	$\phi_{32,2}$	0.042 (0.009) [4.383]
	$\phi_{13,1}$	0.011 (0.002) [6.367]	$\phi_{23,1}$	0.024 (0.005) [4.660]	$\phi_{33,1}$	0.112 (0.006) [16.289]
	$\phi_{13,2}$	-0.001 (0.002) [-0.599]	$\phi_{23,2}$	0.007 (0.005) [1.398]	$\phi_{33,2}$	0.055 (0.007) [7.983]
Adj. R-square	0.192		0.044		0.021	
Akaike Information Criterion	13.598					

Table 18 (A): Granger Causality -- Volatility, Liquidity (Effective Spread) and VPIN.

Table 18 (A) presents the Eviews results from Granger Causality tests for the high-frequency liquidity benchmark -- the Effective Spread, testing whether there is Granger causality relationship between volatility, liquidity and VPIN. The proxy for market volatility is the absolute return. Chi-sq, degree of freedom, P-value, and rejection results are shown in the table. Test is based on Vector Auto-Regression model. Panel A tests for the Granger relationship between liquidity and VPIN; Panel B tests for the Granger relationship between VPIN and volatility; Panel C tests for the Granger relationship between liquidity and volatility.

Null Hypothesis	Chi-sq	df	Prob.	Result
Panel A: Liquidity & VPIN				
Liq. Does not Granger Cause VPIN	8.8091	2	0.012**	**Reject**
VPIN Does not Granger Cause Liq.	26.228	2	0.000***	**Reject**
Panel B: VPIN & Volatility				
VPIN Does not Granger Cause Vol.	55.157	2	0.000***	**Reject**
Vol. does not Granger Cause VPIN	19.948	2	0.000***	**Reject**
Panel C: Liquidity & Volatility				
Liq. Does not Granger Cause Vol.	9.5248	2	0.009***	**Reject**
Vol. Does not Granger Cause Liq.	61.822	2	0.000***	**Reject**

Note: *** indicates that the result is significant at 1%-level, ** indicates that the result is significant at 5%-level, and * indicates the result is significant at 10%-level. The significance is reported based on two-tailed tests.

Table 18 (B): Granger Causality -- Volatility, Liquidity (Realized Spread) and VPIN.

Table 18 (B) presents the Eviews results from Granger Causality tests for the high-frequency liquidity benchmark -- the Realized Spread, testing whether there is Granger causality relationship between volatility, liquidity and VPIN. The proxy for market volatility is the absolute return. Chi-sq, degree of freedom, P-value, and rejection results are shown in the table. Test is based on Vector Auto-Regression model. Panel A tests for the Granger relationship between liquidity and VPIN; Panel B tests for the Granger relationship between VPIN and volatility; Panel C tests for the Granger relationship between liquidity and volatility.

Null Hypothesis	Chi-sq	df	Prob.	Result
Panel A: Liquidity & VPIN				
Liq. Does not Granger Cause VPIN	34.791	2	0.000***	**Reject**
VPIN Does not Granger Cause Liq.	25.489	2	0.000***	**Reject**
Panel B: VPIN & Volatility				
VPIN Does not Granger Cause Vol.	40.588	2	0.000***	**Reject**
Vol. does not Granger Cause VPIN	4.965	2	0.083*	**Reject**
Panel C: Liquidity & Volatility				
Liq. Does not Granger Cause Vol.	715.42	2	0.000***	**Reject**
Vol. Does not Granger Cause Liq.	35.319	2	0.000***	**Reject**

Note: *** indicates that the result is significant at 1%-level, ** indicates that the result is significant at 5%-level, and * indicates the result is significant at 10%-level. The significance is reported based on two-tailed tests.

Table 18 (C): Granger Causality -- Volatility, Liquidity (Quoted Spread) and VPIN.

Table 18 (C) presents the Eviews results from Granger Causality tests for the high-frequency liquidity benchmark -- the Quoted Spread, testing whether there is Granger causality relationship between volatility, liquidity and VPIN. The proxy for market volatility is the absolute return. Chi-sq, degree of freedom, P-value, and rejection results are shown in the table. Test is based on Vector Auto-Regression model. Panel A tests for the Granger relationship between liquidity and VPIN; Panel B tests for the Granger relationship between VPIN and volatility; Panel C tests for the Granger relationship between liquidity and volatility.

Null Hypothesis	Chi-sq	df	Prob.	Result
Panel A: Liquidity & VPIN				
Liq. Does not Granger Cause VPIN	15.286	2	0.001***	Reject
VPIN Does not Granger Cause Liq.	29.469	2	0.000***	Reject
Panel B: VPIN & Volatility				
VPIN Does not Granger Cause Vol.	55.013	2	0.000***	Reject
Vol. does not Granger Cause VPIN	18.331	2	0.000***	Reject
Panel C: Liquidity & Volatility				
Liq. Does not Granger Cause Vol.	21.421	2	0.009***	Reject
Vol. Does not Granger Cause Liq.	90.646	2	0.000***	Reject

Note: *** indicates that the result is significant at 1%-level, ** indicates that the result is significant at 5%-level, and * indicates the result is significant at 10%-level. The significance is reported based on two-tailed tests.

Table 18 (D): Granger Causality -- Volatility, Liquidity (Price Impact) and VPIN.

Table 18 (D) presents the Eviews results from Granger Causality tests for the high-frequency liquidity benchmark -- the Price Impact, testing whether there is Granger causality relationship between volatility, liquidity and VPIN. The proxy for market volatility is the absolute return. Chi-sq, degree of freedom, P-value, and rejection results are shown in the table. Test is based on Vector Auto-Regression model. Panel A tests for the Granger relationship between liquidity and VPIN; Panel B tests for the Granger relationship between VPIN and volatility; Panel C tests for the Granger relationship between liquidity and volatility.

Null Hypothesis	Chi-sq	df	Prob.	Result
Panel A: Liquidity & VPIN				
Liq. Does not Granger Cause VPIN	34.011	2	0.000***	Reject
VPIN Does not Granger Cause Liq.	26.019	2	0.000***	Reject
Panel B: VPIN & Volatility				
VPIN Does not Granger Cause Vol.	40.623	2	0.000***	Reject
Vol. does not Granger Cause VPIN	5.1469	2	0.076*	Reject
Panel C: Liquidity & Volatility				
Liq. Does not Granger Cause Vol.	707.52	2	0.000***	Reject
Vol. Does not Granger Cause Liq.	34.486	2	0.000***	Reject

Note: *** indicates that the result is significant at 1%-level, ** indicates that the result is significant at 5%-level, and * indicates the result is significant at 10%-level. The significance is reported based on two-tailed tests.

Appendix D -- Figures

Figure 1: U.S. Equity Indices and Equity Index Futures, May 6, 2010.

Figure is quoted from CFTC-SEC Report "Preliminary Findings Regarding the Market Events of May 6, 2010". This figure shows the transaction prices of Dow Jones Industrial Average, E-Mini S&P 500, and S&P 500 Index from 9:30 to 16:00 on May 6th, 2010.

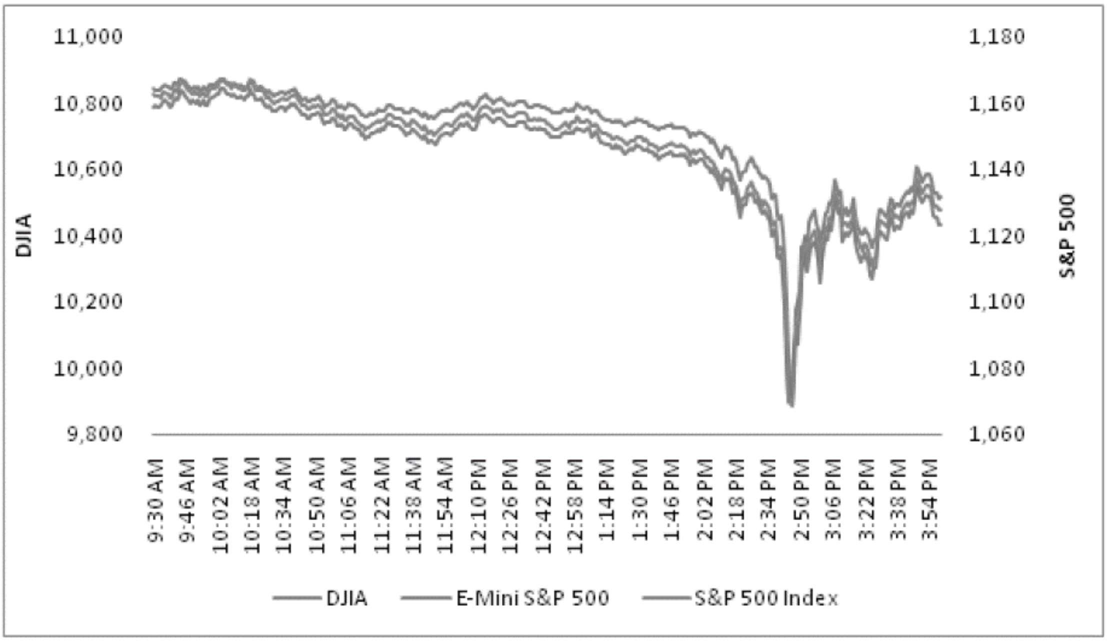

Figure 2: Sequential Trading Diagram of 1996 PIN Model.

Figure is quoted from EKOP (1996). This figure shows us the basic structure of trading process, which is a basic frame of PIN and VPIN model. In this model, α is the probability of an information event, representing news happening; δ is the probability of a low signal, representing bad news happening; μ is the rate of uninformed buy and sell trade arrivals; ε is the rate of uninformed buy and sell trade arrivals.

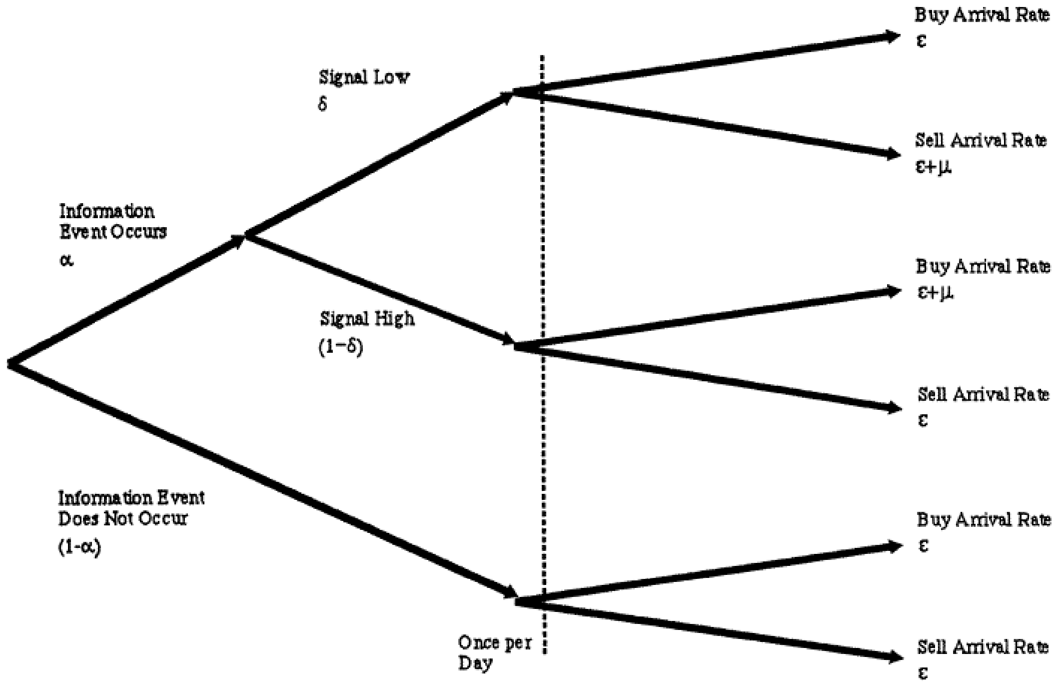

Figure 3 (a): BV-VPIN of Year 2012 -2013.

Figure 3 (a) graphs BV-VPIN statistics of Chinese Stock Index Futures market using SAS software. The period is from January 1, 2012 to December 31, 2013.

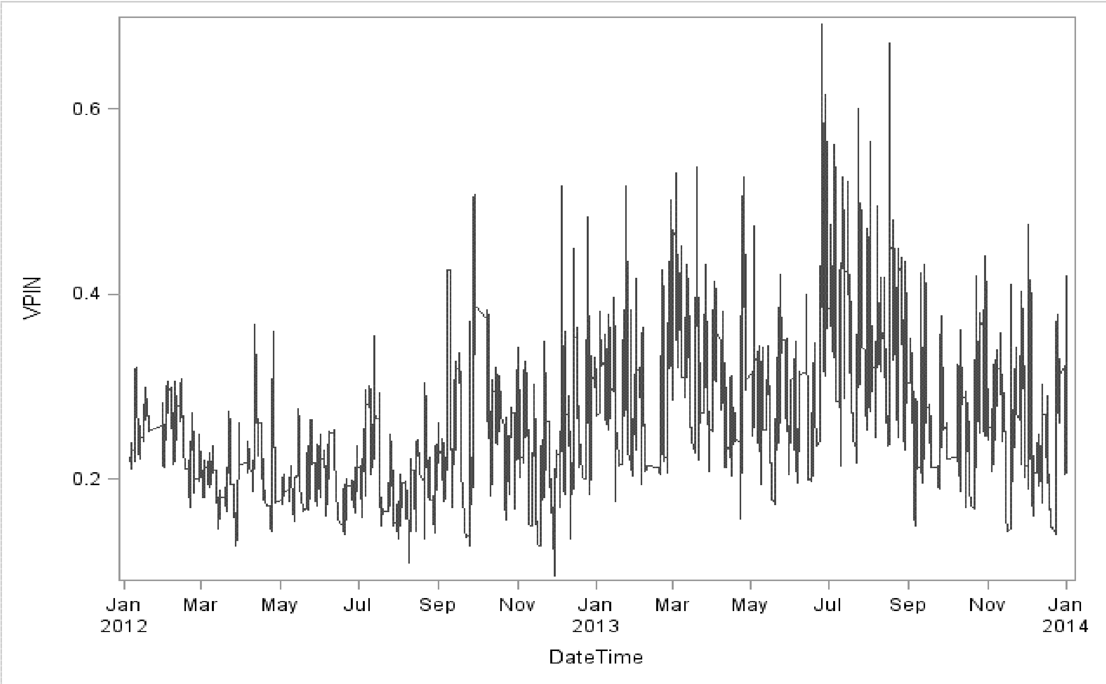

Figure 3 (b): Historical Distribution of BV-VPIN on Year 2012 - 2013.

Figure 3 (b) shows the historical distribution of BV-VPIN on the year 2012 - 2013 of Chinese Stock Index Futures market.

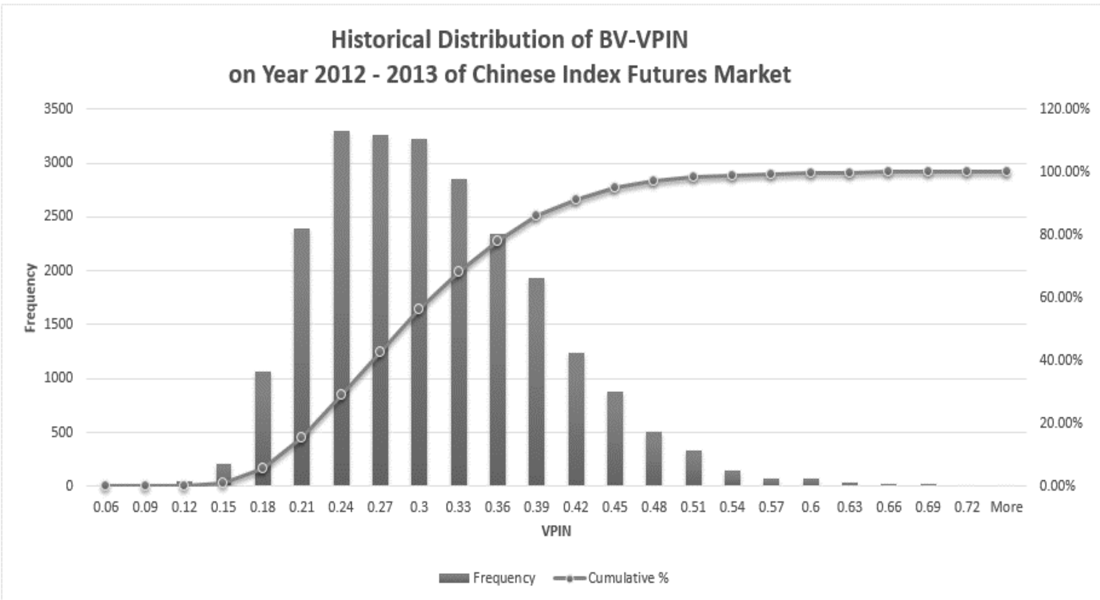

Figure 4 (a): TR-VPIN of Year 2012 -2013.

Figure 4 (a) graphs TR-VPIN statistics of Chinese Stock Index Futures market using SAS software. The period is from January 1, 2012 to December 31, 2013.

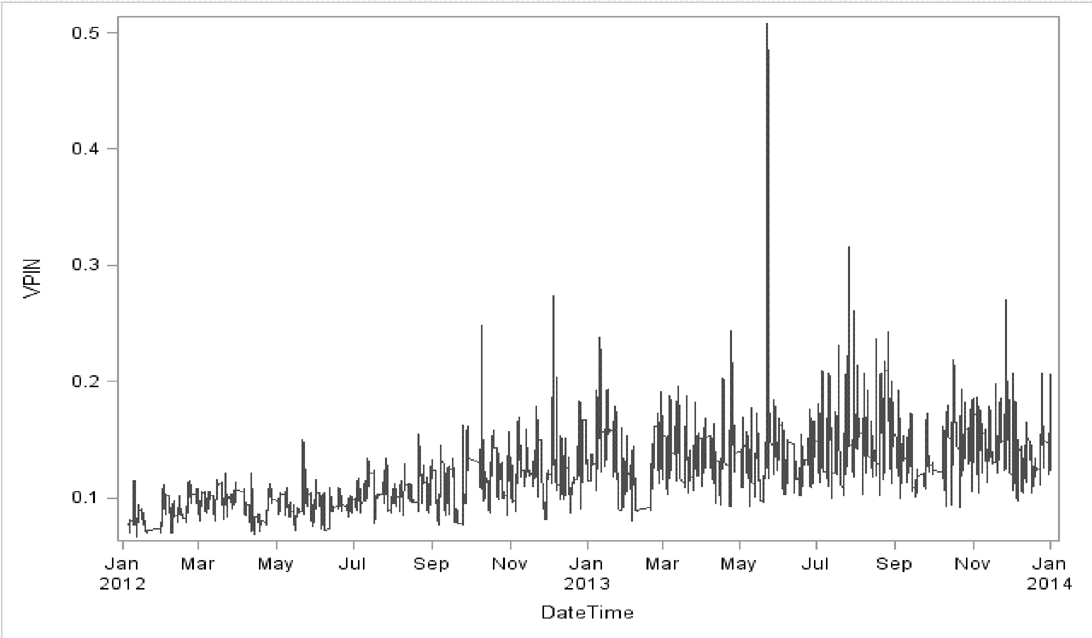

Figure 4 (b): Historical Distribution of TR-VPIN on Year 2012 - 2013.

Figure 4 (b) shows the historical distribution of TR-VPIN on the year 2012 - 2013 of Chinese Stock Index Futures market.

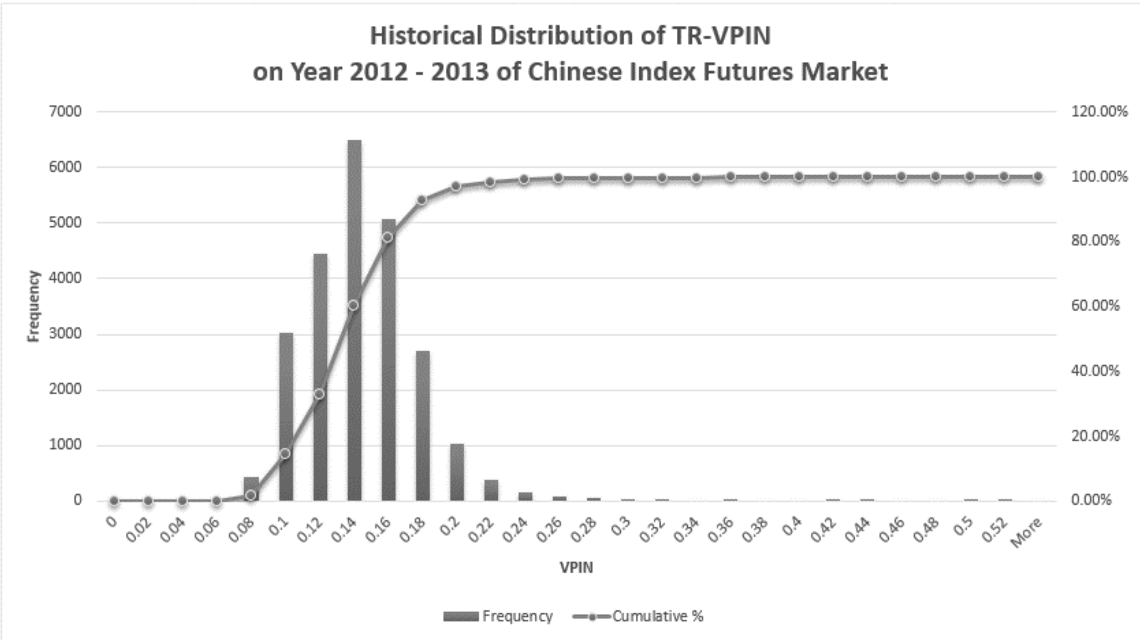

Figure 5 (a): LR-VPIN of Year 2012 -2013.

Figure 5 (a) graphs LR-VPIN statistics of Chinese Stock Index Futures market using SAS software. The period is from January 1, 2012 to December 31, 2013.

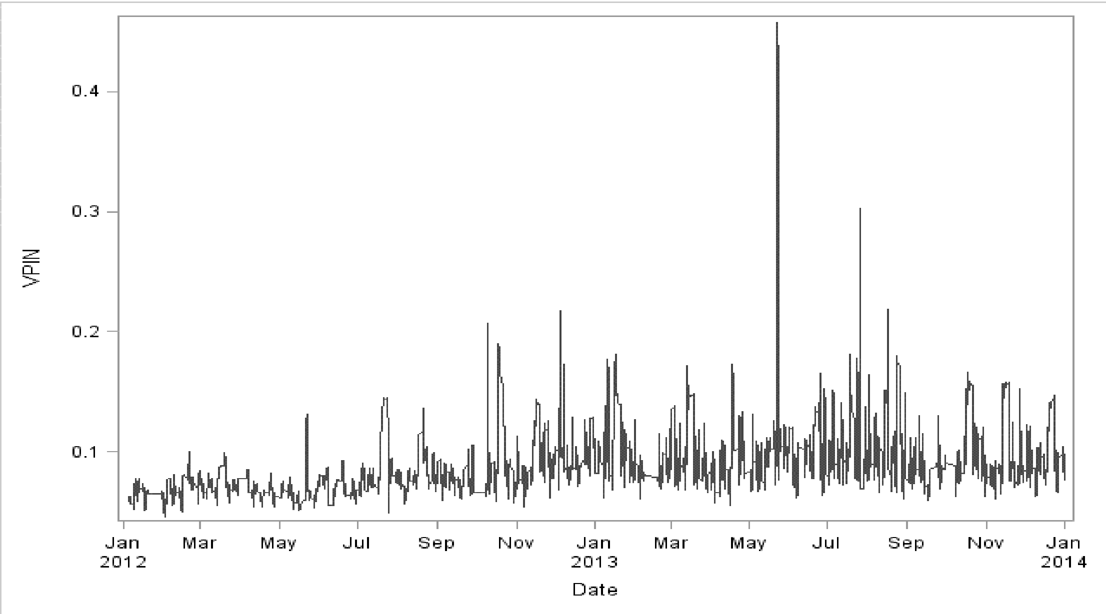

Figure 5 (b): Historical Distribution of LR-VPIN on Year 2012 - 2013.

Figure 5 (b) shows the historical distribution of LR-VPIN on the year 2012 - 2013 of Chinese Stock Index Futures market.

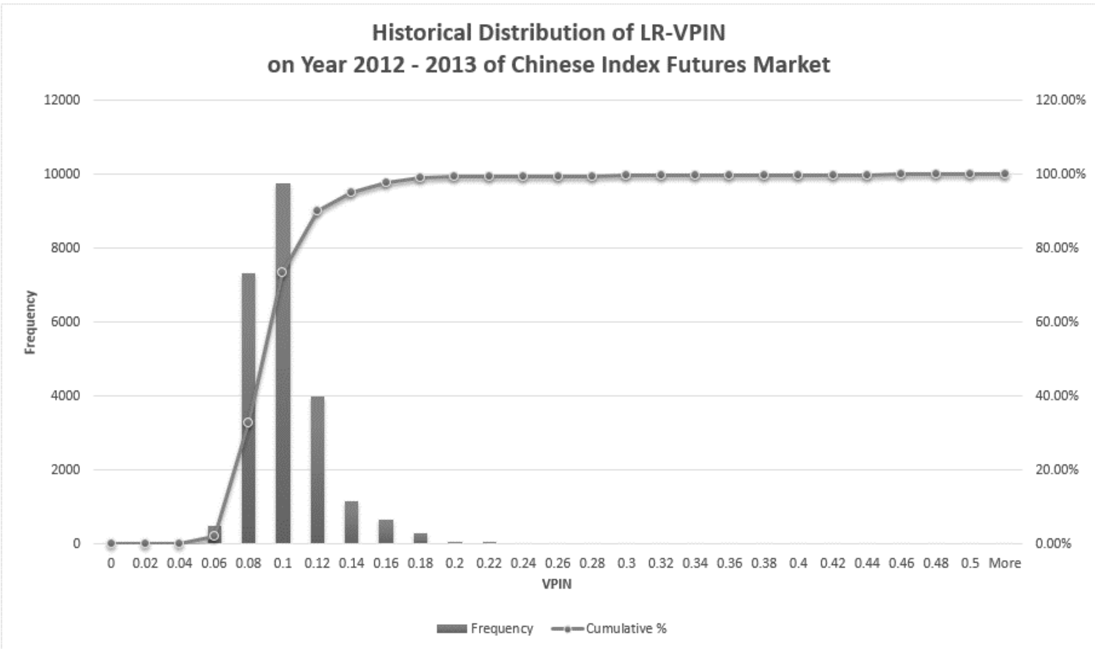

Figure 6 (a): BV-VPIN on August 16, 2013.

Figure 6 (a) demonstrates the BV-VPIN of Chinese Stock Index Futures Market on August 16, 2013. The orange curve stands for the price, the red curve stands for VPIN, and the blue curve stands for the CDF of VPIN.

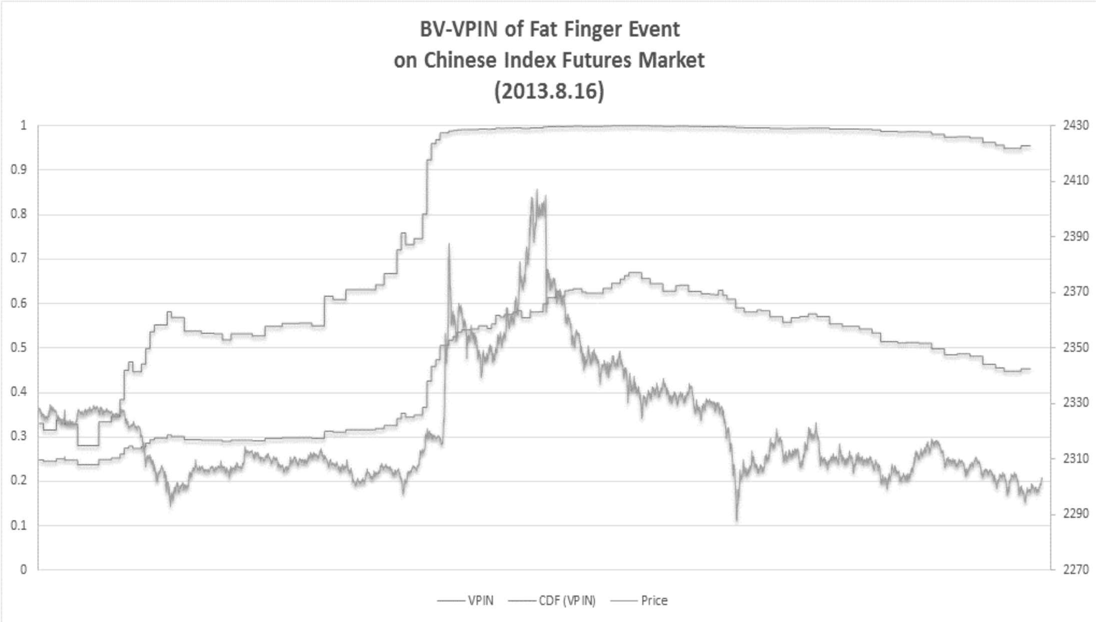

Figure 6 (b): TR-VPIN on August 16, 2013.

Figure 6 (b) demonstrates the TR-VPIN of Chinese Stock Index Futures Market on August 16, 2013. The orange curve stands for the price, the red curve stands for VPIN, and the blue curve stands for the CDF of VPIN.

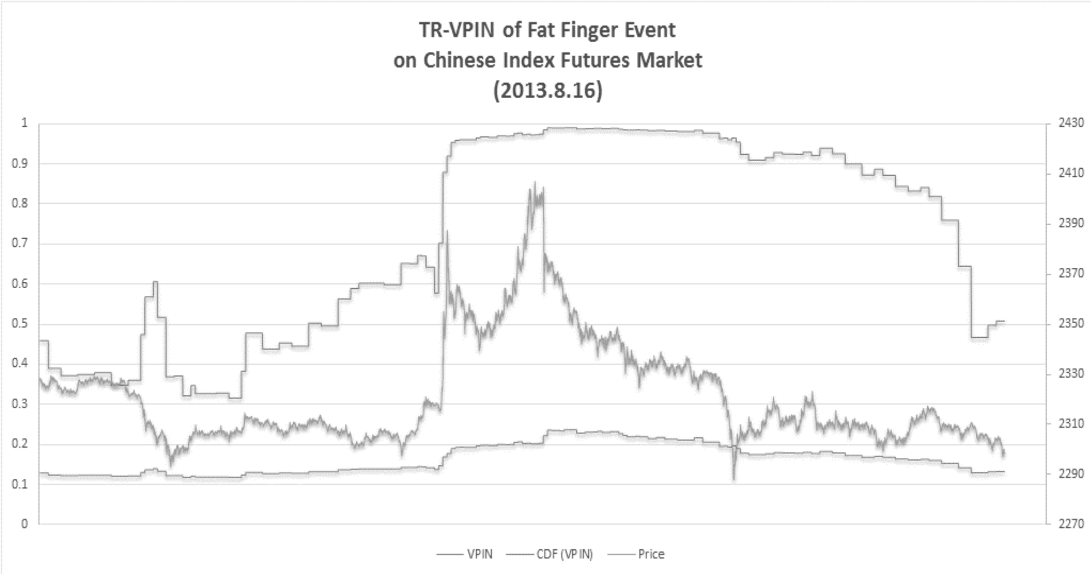

Figure 6 (c): LR-VPIN on August 16, 2013.

Figure 6 (c) demonstrates the LR-VPIN of Chinese Stock Index Futures Market on August 16, 2013. The orange curve stands for the price, the red curve stands for VPIN, and the blue curve stands for the CDF of VPIN.

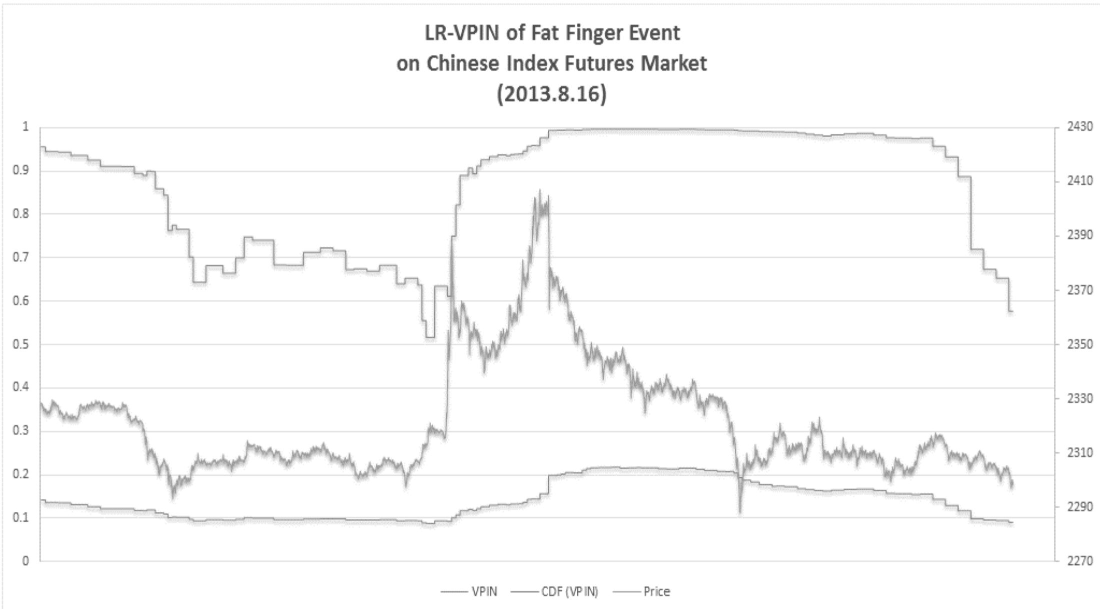

Figure 7 (a): BV-VPIN on June 24, 2013 to June 25, 2013.

Figure 7 (a) shows the BV-VPIN of Chinese Stock Index Futures Market on June 24, 2013 to June 25, 2013. The green curve stands for the price, the blue curve stands for VPIN, and the red curve stands for the CDF of VPIN.

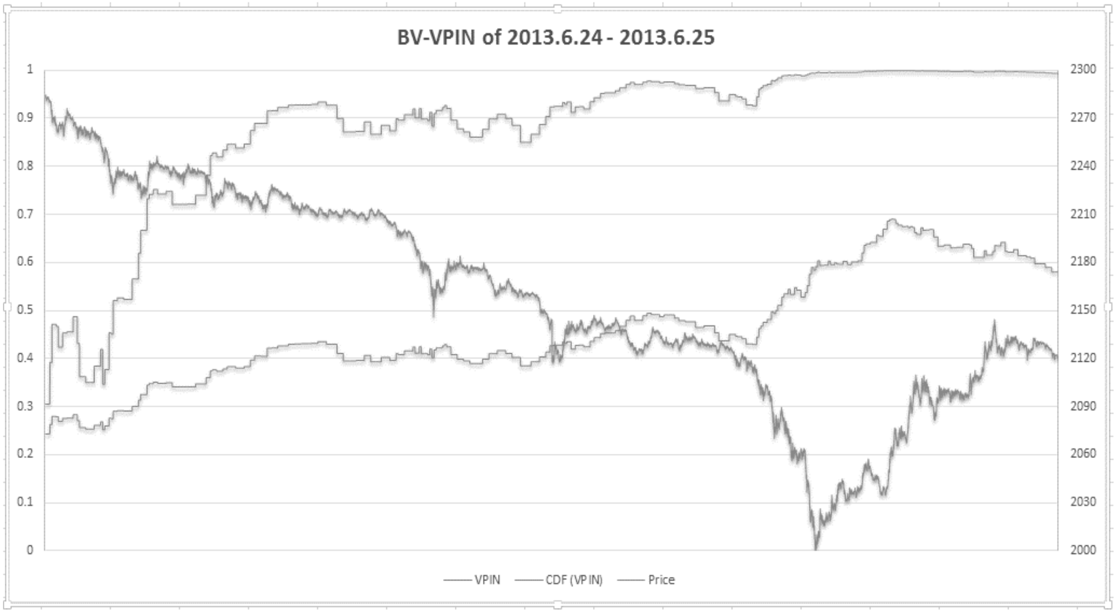

Figure 7 (b): BV-VPIN on June 17, 2013 to June 28, 2013.

Figure 7 (b) shows the BV-VPIN of Chinese Stock Index Futures Market on June 17, 2013 to June 28, 2013. The green curve stands for the price, the blue curve stands for VPIN, and the red curve stands for the CDF of VPIN.

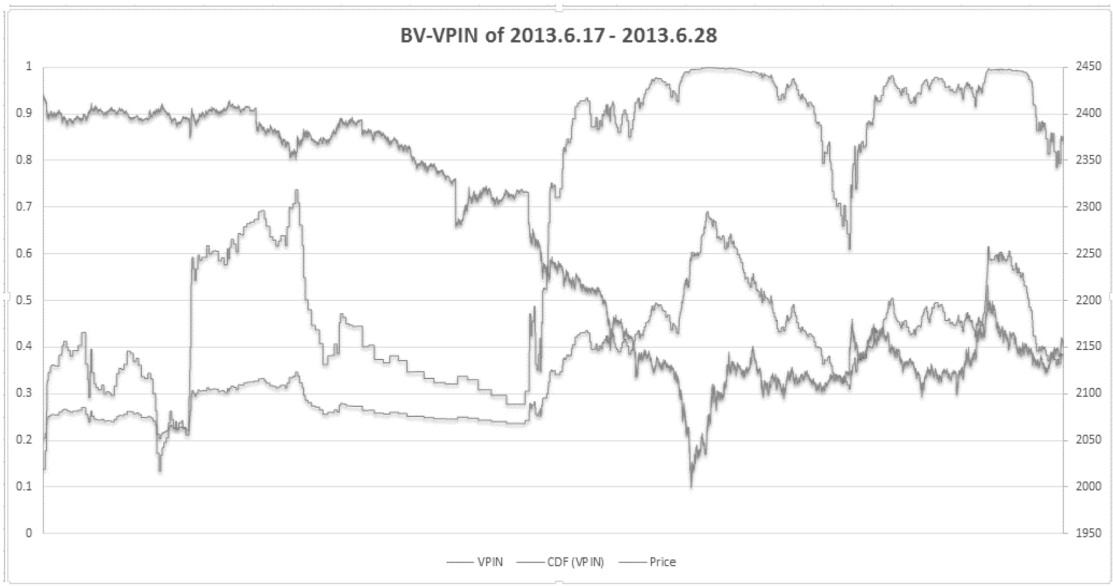

Figure 8 (a): TR-VPIN on June 24, 2013 to June 25, 2013.

Figure 8 (a) expresses the TR-VPIN of Chinese Stock Index Futures Market on June 24, 2013 to June 25, 2013. The green curve stands for the price, the blue curve stands for VPIN, and the red curve stands for the CDF of VPIN.

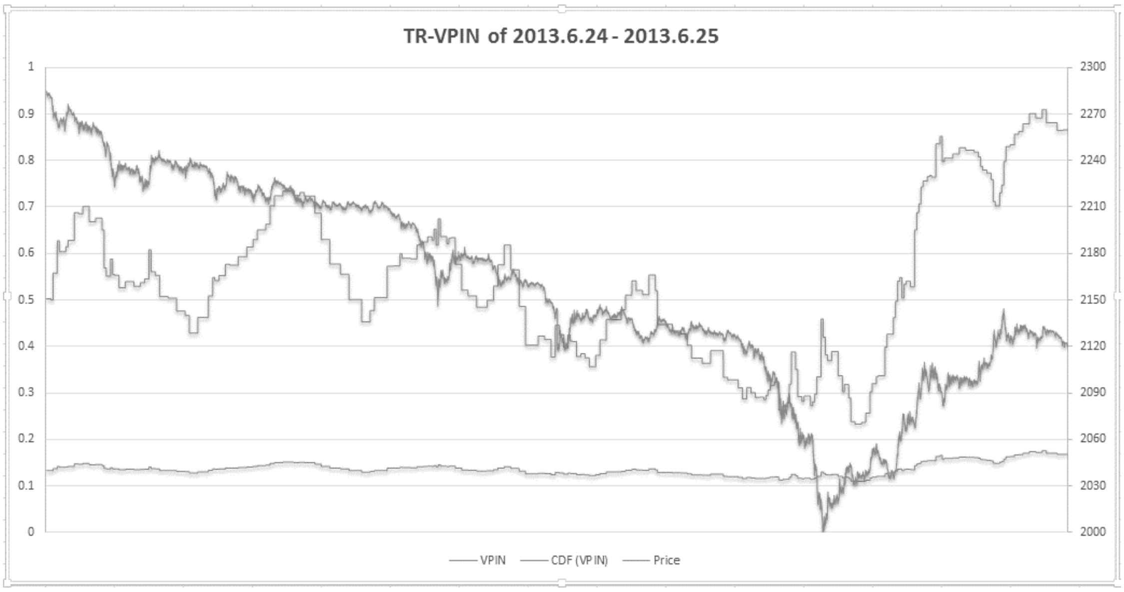

Figure 8 (b): TR-VPIN on June 17, 2013 to June 28, 2013.

Figure 8 (b) expresses the TR-VPIN of Chinese Stock Index Futures Market on June 17, 2013 to June 28, 2013. The green curve stands for the price, the blue curve stands for VPIN, and the red curve stands for the CDF of VPIN.

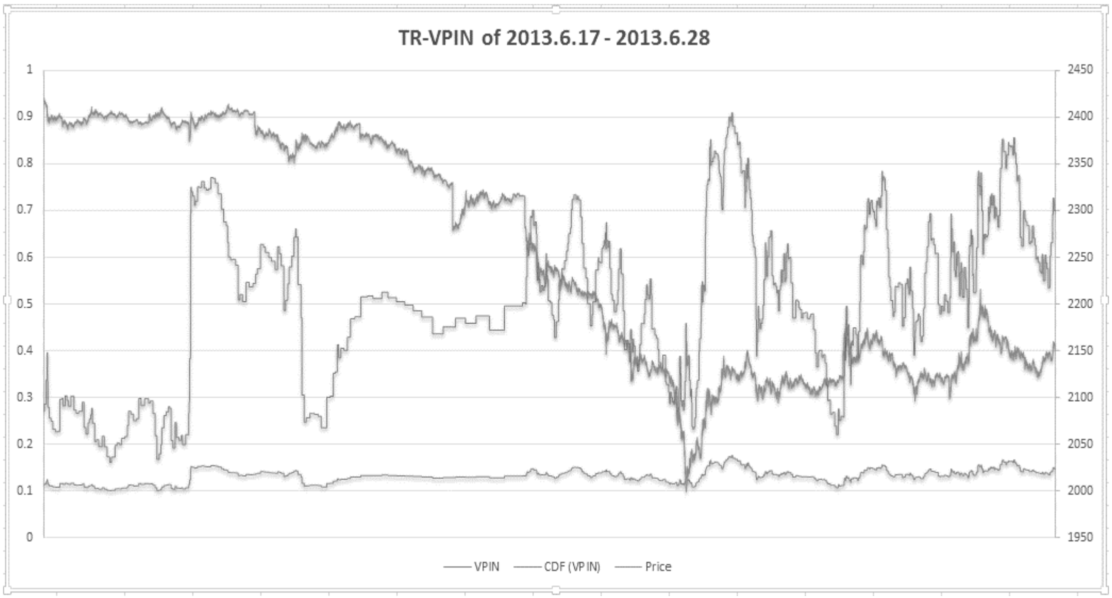

Figure 9 (a): LR-VPIN on June 24, 2013 to June 25, 2013.

Figure 9 (a) expresses the LR-VPIN of Chinese Stock Index Futures Market on June 24, 2013 to June 25, 2013. The green curve stands for the price, the blue curve stands for VPIN, and the red curve stands for the CDF of VPIN.

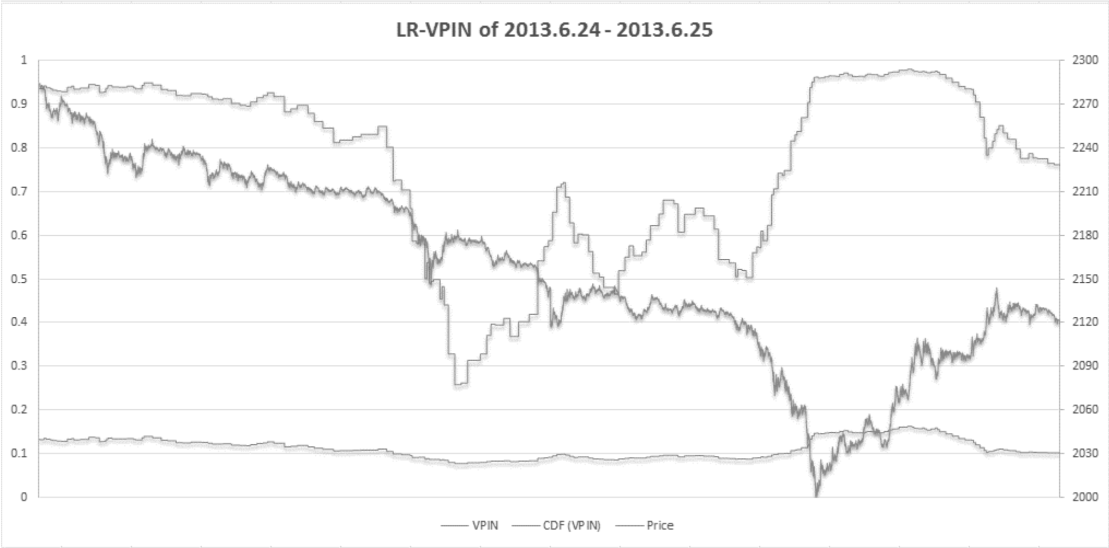

Figure 9 (b): LR-VPIN on June 17, 2013 to June 28, 2013.

Figure 9 (b) expresses the TR-VPIN of Chinese Stock Index Futures Market on June 17, 2013 to June 28, 2013. The green curve stands for the price, the blue curve stands for VPIN, and the red curve stands for the CDF of VPIN.

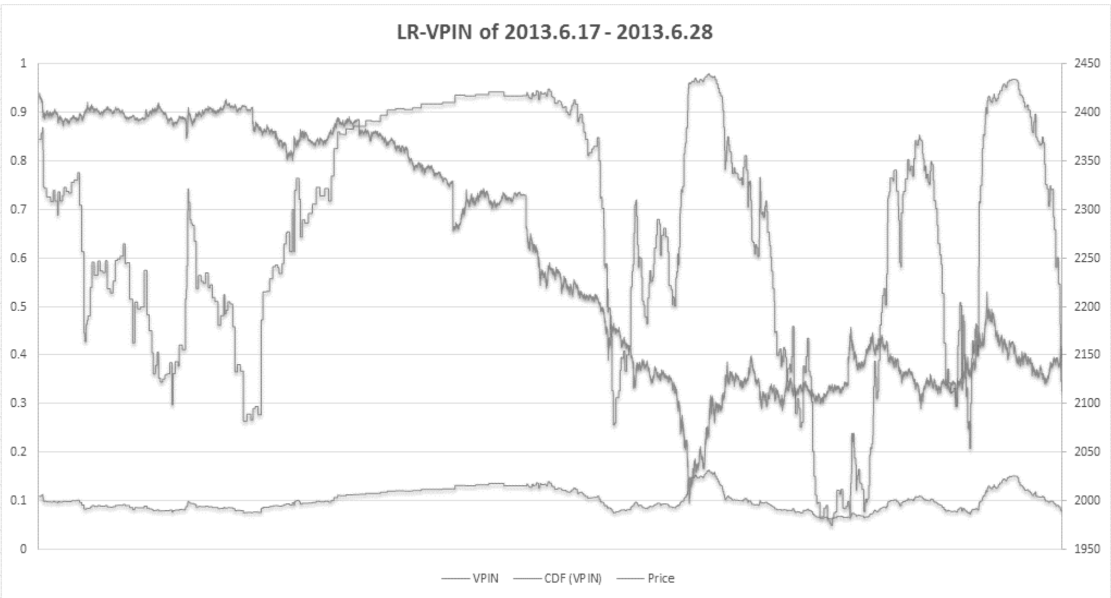

Figure 10 (a): Robustness Check of BV-VPIN: 1-1-5.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 1-min time bar, 1 bucket to compute the VBS, and 5 buckets of sample length.

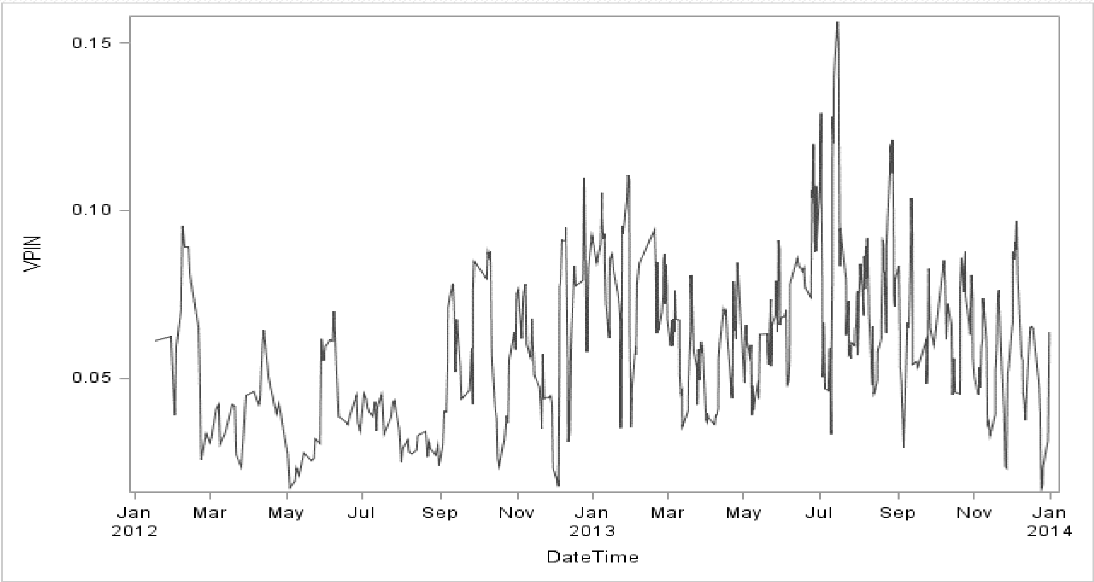

Figure 10 (b): Robustness Check of BV-VPIN: 1-1-20.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 1-min time bar, 1 bucket to compute the VBS, and 20 buckets of sample length.

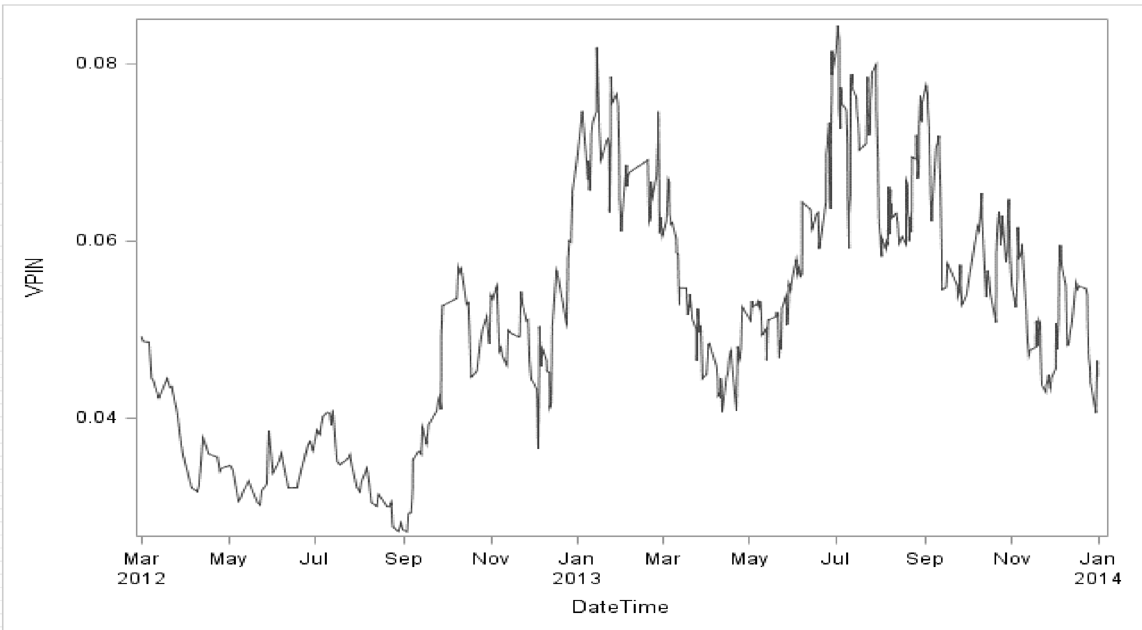

Figure 10 (c): Robustness Check of BV-VPIN: 1-50-50.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 1-min time bar, 50 buckets to compute the VBS, and 50 buckets of sample length.

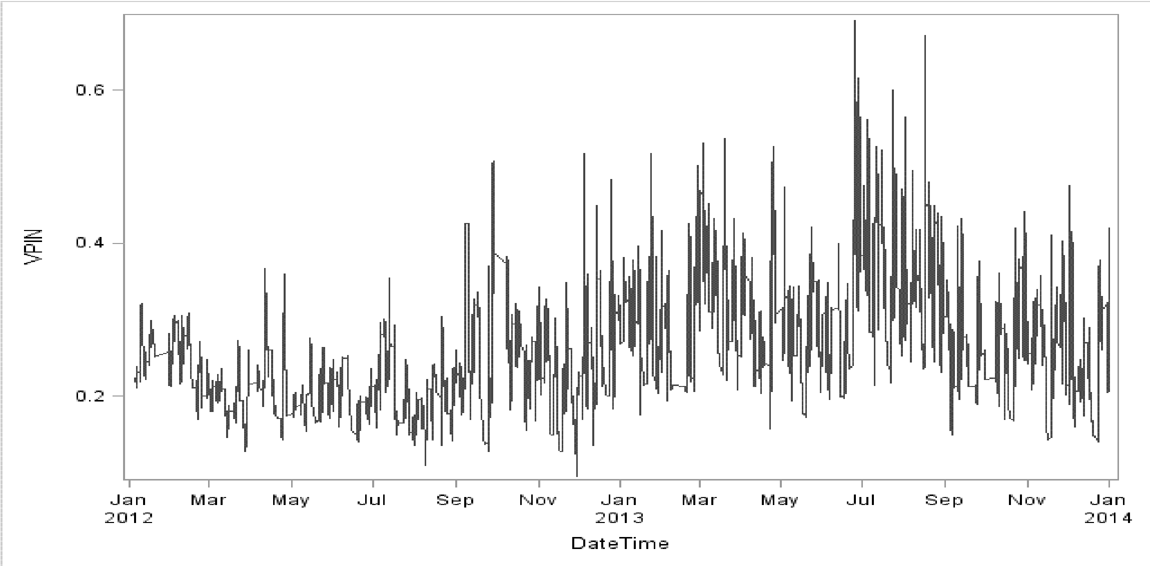

Figure 10 (d): Robustness Check of BV-VPIN: 1-50-250.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 1-min time bar, 50 buckets to compute the VBS, and 250 buckets of sample length.

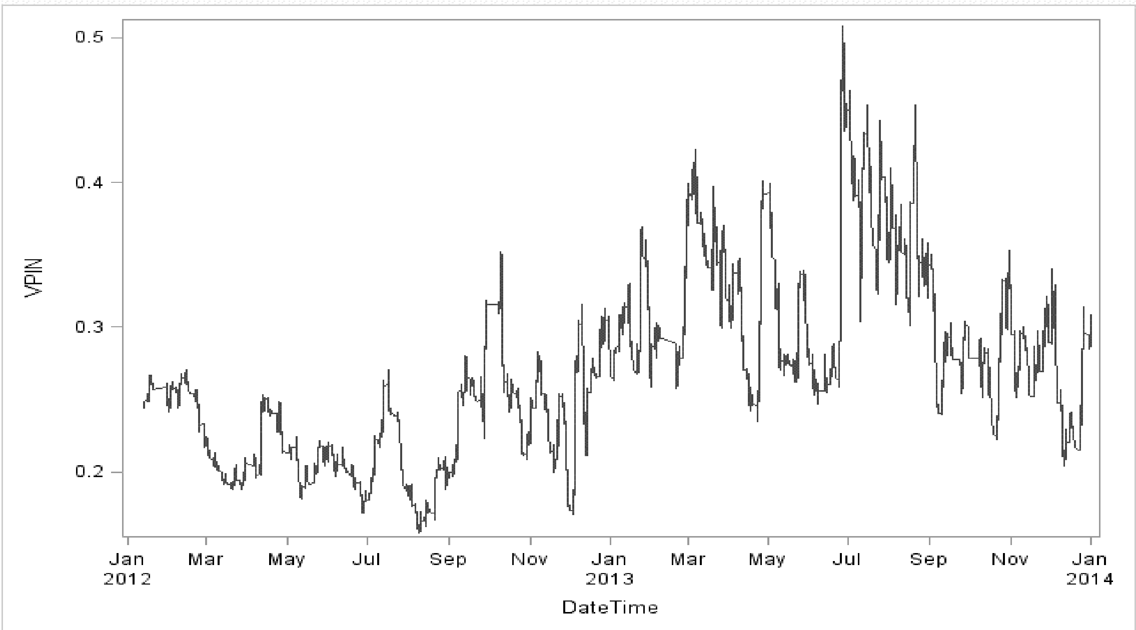

Figure 10 (e): Robustness Check of BV-VPIN: 5-1-5.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 5-min time bar, 1 bucket to compute the VBS, and 5 buckets of sample length.

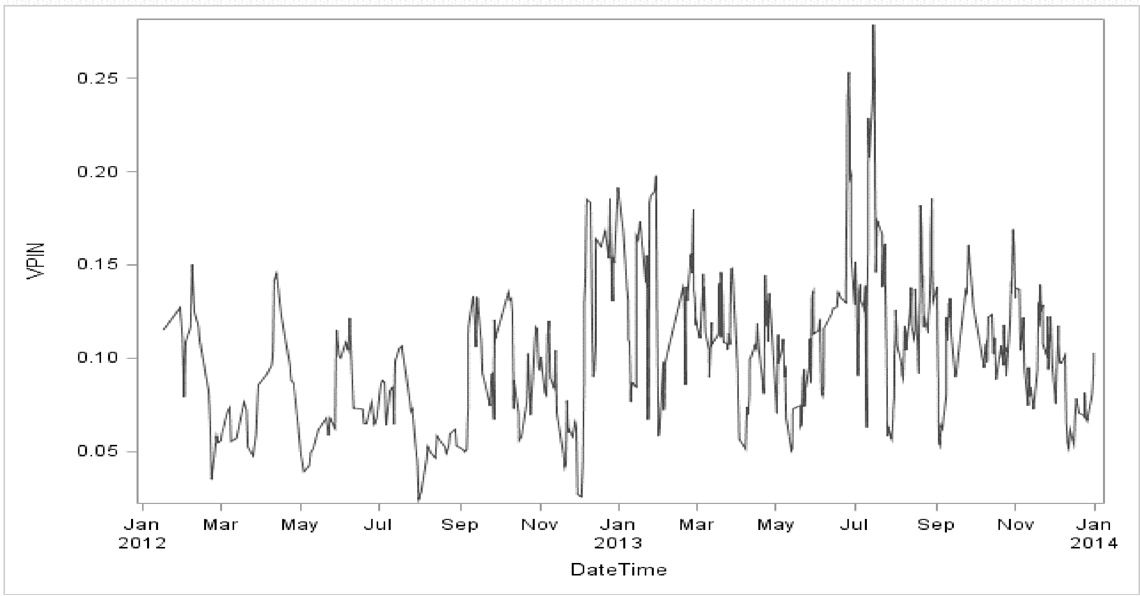

Figure 10 (f): Robustness Check of BV-VPIN: 5-1-20.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 5-min time bar, 1 bucket to compute the VBS, and 20 buckets of sample length.

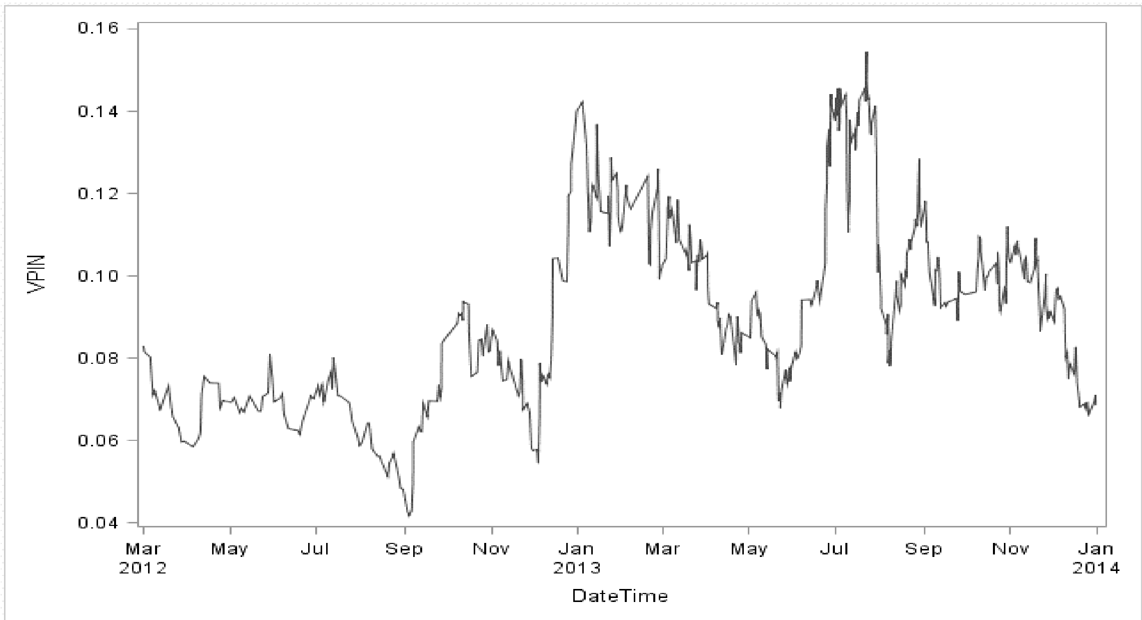

Figure 10 (g): Robustness Check of BV-VPIN: 5-50-50.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 5-min time bar, 50 bucket to compute the VBS, and 50 buckets of sample length.

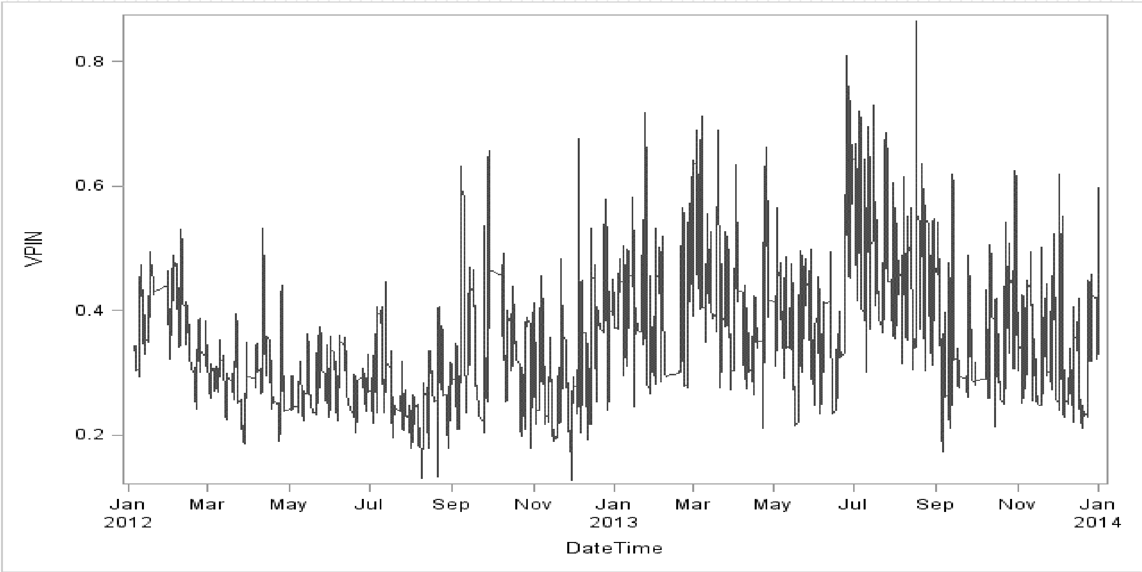

Figure 10 (h): Robustness Check of BV-VPIN: 5-50-250.

The stability of VPIN metric is checked under different volume classification schemes. In this SAS figure, we use 5-min time bar, 50 buckets to compute the VBS, and 250 buckets of sample length.

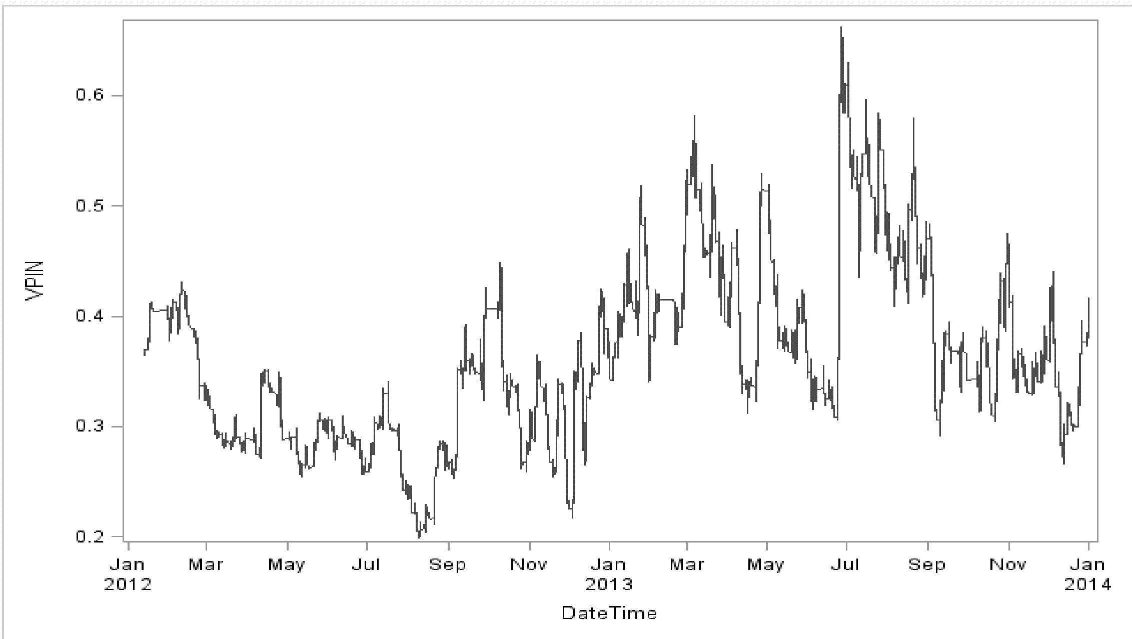

Figure 11 (a): Impulse Response of VPIN Given the Shock of Realized Spread.

Figure shows Eviews result of the impulse response analysis of VPIN to the shock of a high-frequency liquidity benchmark -- the realized spread. 10 periods are chosen for this test. The horizontal axis stands for liquidity, while the vertical axis stands for the response of VPIN. The blue curve states the impulse response of VPIN to the realized spread, with the two red curves adds the standard errors. Sample is on Chinese Stock Index Futures market, from January 1st, 2012 to December 31th, 2013.

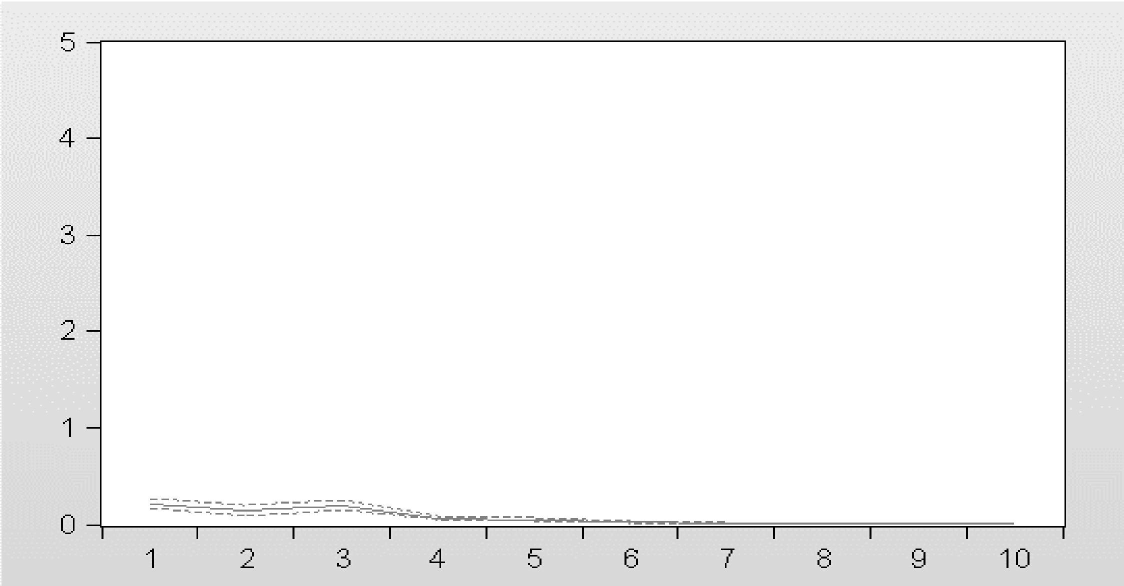

Figure 11 (b): Impulse Response of the Realized Spread Given the Shock of VPIN.

Figure shows Eviews result of the impulse response analysis of the realized spread to the Shock of VPIN. 10 periods are chosen for this test. The horizontal axis stands for VPIN, while the vertical axis stands for the response of liquidity. The blue curve states the impulse response of the realized spread to VPIN, with the two red curves adds the standard errors. Sample is on Chinese Stock Index Futures market, from January 1st, 2012 to December 31th, 2013.

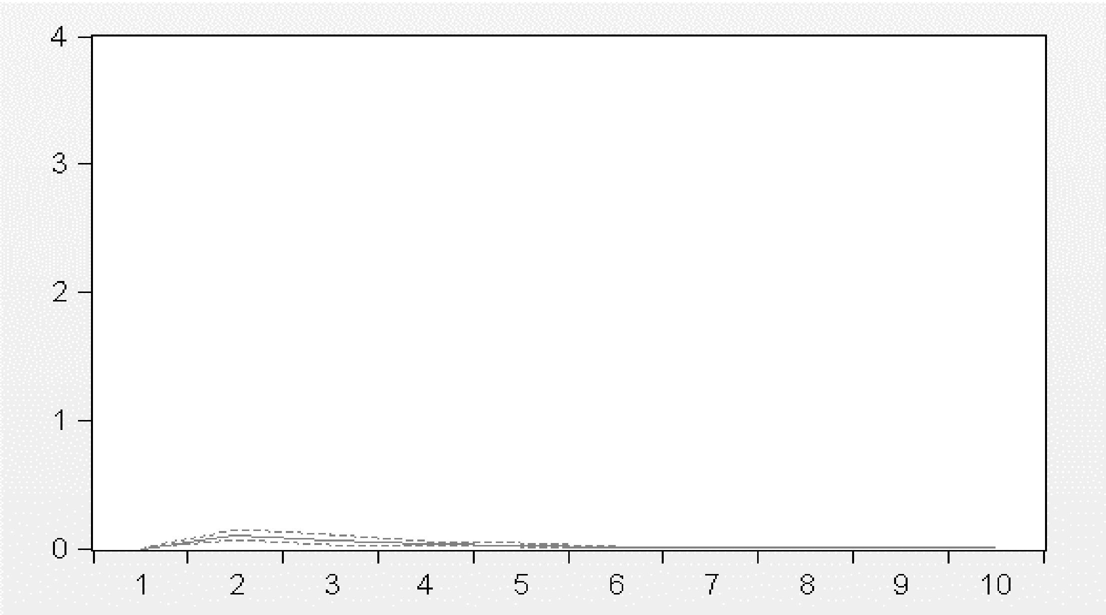

Figure 12 (a): Impulse Response of VPIN Given the Shock of the Realized Spread -- the Fat Finger Event.

Figure shows Eviews result of the impulse response analysis of VPIN to a high-frequency liquidity benchmark -- the realized spread. 10 periods are chosen for this test. The horizontal axis stands for liquidity, while the vertical axis stands for the response of VPIN. The blue curve states the impulse response of VPIN to the realized spread, with the two red curves adds the standard errors. Sample is from Chinese Stock Index Futures market on the day of Aug 16, 2013.

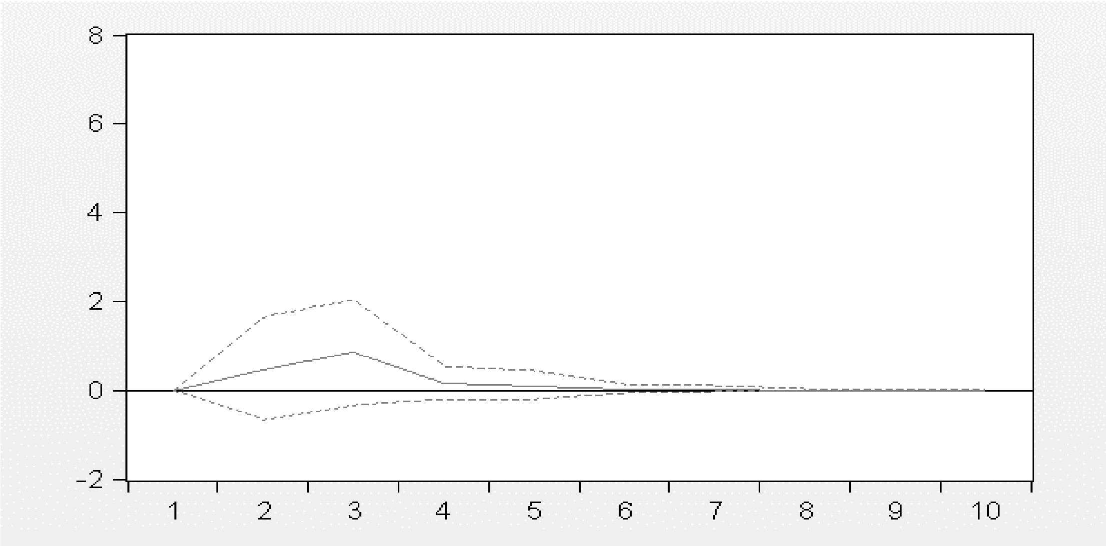

Figure 12 (b): Impulse Response of the Realized Spread Given the Shock of VPIN -- the Fat Finger Event.

Figure shows Eviews result of the impulse response analysis of the realized spread to VPIN. 10 periods are chosen for this test. The horizontal axis stands for VPIN, while the vertical axis stands for the response of liquidity. The blue curve states the impulse response of the realized spread to VPIN, with the two red curves adds the standard errors. Sample is from Chinese Stock Index Futures market on the day of Aug 16, 2013.